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Quality Assessment of the Canadian OpenStreetMap Road Networks

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Abstract

Volunteered geographic information (VGI) has been applied in many fields such as participatory planning, humanitarian relief and crisis management because of its cost-effectiveness. However, coverage and accuracy of VGI cannot be guaranteed. OpenStreetMap (OSM) is a popular VGI platform that allows users to create or edit maps using GPS-enabled devices or aerial imageries. The issue of geospatial data quality in OSM has become a trending research topic because of the large size of the dataset and the multiple channels of data access. The objective of this study is to examine the overall reliability of the Canadian OSM data. An extensive review is first presented to provide details on the quality evaluation process of OSM. A case study of London, Ontario is followed as an experimental analysis of completeness, positional accuracy and attribute accuracy of the OSM street networks. Next, a national study of the Canadian OSM data assesses the overall semantic accuracy and lineage in addition to the quality measures mentioned above. Results of the quality evaluation are compared with associated OSM provenance metadata to examine potential correlations. The Canadian OSM road networks were found to have comparable accuracy with the tested commercial database (DMTI). Although statistical analysis suggests that there are no significant relations between OSM accuracy and its editing history, the study presents the complex processes behind OSM contributions possibly influenced by data import and remote mapping. The findings of this thesis can potentially guide cartographic product selection for interested parties and offer a better understanding of future quality improvement in OSM.

Keywords

Volunteered geographic information, OpenStreetMap, Canada, quality

Co-Authorship Statement

This thesis was prepared according to the integrated-article format developed by the School of Graduate and Postdoctoral Studies at Western University, London, Ontario, Canada. All the work stated in this thesis including literature review, methodology design, data analysis and manuscript writing was fully undertaken by the author. Dr. Jacek Malczewski provided insightful revision suggestions as the supervisor. Versions of Chapters 2 and 3 have been published, accepted or submitted as co-authored peer-reviewed book chapters or journal articles.

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List of Abbreviations

AA	Attribute Accuracy
API	Application Programming Interface
ATKIS	German Authority Topographic-Cartographic Information System
BD TOPO	Topographic datasets from the French National Institute of Geography
BKG	German Federal Agency for Cartography and Geodesy
BOINC	Berkeley Open Infrastructure for Network Computing
C	Completeness
CC BY-SA	Creative Commons License Attribution-ShareAlike
CGI	Contributed Geographic Information
CLC	Corine Land Cover database
CMA	Census Metropolitan Area
DMTI	Digital Mapping Technologies Inc.
GIS	Geographic Information Science
GMESUA	Global Monitoring for Environment and Security Urban Atlas
GPS	Global Positioning System
GTA	Great Toronto Area
GWR	Geographically Weighted Regression
HOT	Humanitarian OpenStreetMap Team
IBGE	Brazilian Institute of Geography and Statistics
IRC	Internet Relay Chats
ISO	International Organization for Standardization
ITN	Integrated Transport Network
JOSM	Java OpenStreetMap Editor
L	Lineage
LBS	Location-Based Services
LC	Logical Consistency
LD	Levenshtein Distance
LISA	Local Indicators of Spatial Associations
LOD	Level of Details
N/A	Not Available

NMA	National Mapping Agencies (South Africa)
NRN	National Road Network (Canada)
ODbL	Open Database License
OLS	Ordinary Least Squares
ORNL	Oak Ridge National Laboratory
OS	Ordnance Survey, the national mapping agency for Great Britain
OSM	OpenStreetMap
PA	Positional Accuracy
PBF	Protocol Buffer Binary Format
POI	Point of Interest
PPGIS	Public Participation Geographic Information System
RDF	Resource Description Framework
RFSN	Reputation-based Framework for High Integrity Sensor Networks
SA	Semantic Accuracy
TIGER/Line	Topologically Integrated Geographic Encoding and Referencing (US)
TQ	Temporal Quality
UGC	User-Generated Content
UID	Unique Identifier
UK	United Kingdom
US	United States
VGI	Volunteered Geographic Information
VMD	Vector Map District
XML	Extensible Markup Language

Chapter 1

1 Introduction

Advancing technologies, such as the Global Positioning System (GPS), the gigabit internet, and Web 2.0, have proliferated the amount of user-generated content (UGC) online. More and more quantitative geographers have since used data mining and other nontraditional GIS techniques to solve spatial problems. Because of this situation, some geographers have argued that we are now in the world of neogeography (J. Jackson, 2006; Turner, 2006). Nongeographers have contributed so-called “big data” with geotagged information, and only computing-intensive methods may decipher the complex geographic forms and processes behind observed spatial patterns (Jiang, 2013). To describe the amalgamation of citizen participation and GIScience, multiple similar concepts have been proposed (See et al., 2016), and volunteered geographic information (VGI) is one of the widely-accepted terminologies (Goodchild, 2007).

1.1 Volunteered geographic information (VGI)

The term VGI is used to describe user-generated geospatial content. In contrast to contributed geographic information (CGI) with an opt-out agreement (e.g., Google Flu Trends data), VGI is under an opt-in provision (Harvey, 2013). The economic value of VGI is simply a price tag that is accepted by consumers, while the social value of VGI can be reflected in its vital effects in crisis mapping and humanitarian relief (Feick & Roche, 2013). The theory of collective intelligence also applies to VGI, which suggests that a group contribution is better than the best individual outcome (Spielman, 2014). According to Bordogna, Carrara, Criscuolo, Pepe, & Rampini (2016) and Connors, Lei, & Kelly (2012), Table 1 (adapted from Bordogna et al., 2016) lists the categories of VGI/CGI projects. Although some listed projects, such as distributed computing, fall into the crowdsourcing paradigm, geospatial content may still be contributed in those projects.

The popular VGI platform OpenStreetMap (OSM) was founded in August 2004 by Steve Coast with its original focus on mapping the U.K. (OpenStreetMap, 2017d). The project is in the field of geography and cartography, requires object identification, observation measurement, and transcription, implements mixed strategies of information creation, has a high need for VGI, and contains all types of volunteers except for those who are unaware of their contributions. In the initial years of the project, mapping data were mainly contributed using GPS-enabled devices. However, the availability of satellite images on OSM since 2007 has led to the prevalence of “armchair mapping”. Remote mappers without local knowledge have contributed a large amount of data without identify themselves as nonlocal contributors. Therefore, a project like OSM has unpredictable quality because of its mixed methods of VGI creation.

Table 1. Categories of VGI/CGI projects

Categories		Examples
Scientific field	Computer science	Scientific computing
	Natural science	Weather forecast
	Medicine/Biology	Genetics
	Social science	Cultural heritage
Volunteer's task	Massive computer time	Berkeley Open Infrastructure for Network Computing (BOINC) software for distributed computing
	Specific human abilities	Galaxy Zoo project[1] for classifying the shapes of galaxies in deep field images
	Objects identification	eBird project[2] for observing species of birds
	Observation measurement	'Did You Feel It?' web service[3] for gathering citizens' experience of earthquakes
	Transcription	Old Weather project[4] for loading historical weather data into geodatabase
	User indication	SuScit – Citizen Science for sustainability project[5] for collecting local communities' voices in urban sustainability research
	Complementary information	1001 Stories of Denmark project[6] for linking heritages to personal stories
Way of VGI creation	Automatic and implicit	Distributed computing
	Manual and implicit	Google Flu Trends[7] uses aggregated Google search data
	Manual and explicit	Galaxy Zoo project asks scores of confidence
	Automatic and explicit	CoCoRaHS project[8] provides training for volunteers who collect precipitation measurements
	Mixed strategy	OpenStreetMap
Need for VGI	Low	Geoinformation has additional but not essential values in the projects
	Medium	eBird project
	High	OpenStreetMap
Characteristics of volunteer	Neophyte	Volunteers with no official background
	Interested amateur	Volunteers with some experience
	Expert amateur	Volunteers with professional skills and expertise
	Expert authority	Volunteers with extensive experience
	Unaware volunteers	Volunteers who are unaware of their contributions

1.2 Quality measures and quality indicators

The history of research in geoinformation quality started in the 1980s (Goodchild & Gopal, 1989), with attention to the quality standards of spatial data (Guptill & Morrison, 2013) and error measurement in cartography (Maling, 2016). In VGI, quality measures and quality indicators are the extrinsic and intrinsic quality evaluation methods (Antoniou & Skopeliti, 2015). While quality measures are derived from the associated ISO standards (see Table 2), quality indicators are the implicit proxies of VGI quality measurement (see Table 3) (Senaratne, Mobasheri, Ali, Capineri, & Haklay, 2016; Van Oort, 2006). Among all criteria, it is very important to study the provenance of VGI because provenance documents the process of error propagation, substitutes missing attributes of map features using previous information, and identifies sources of contributors for perceptual quality assessment (Frew, 2007).

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[1] http://www.galaxyzoo.org/

[2] http://ebird.org/

[3] https://earthquake.usgs.gov/data/dyfi/

[4] https://www.oldweather.org/

[5] http://www.urbansustainabilityexchange.org.uk/ISSUESOutputSuScit.html

[6] http://www.kulturarv.dk/1001fortaellinger/en_GB

[7] https://www.google.org/flutrends/about/

[8] http://www.cocorahs.org/

Table 2. Quality measures for VGI

Categories	Specifications	Descriptions
Comprehensiveness	Completeness	Measures errors of omission (missing data) and commission (extra information)
Accuracy	Positional accuracy	Measures relative and absolute accuracy of coordinate values
	Attribute accuracy	Measures classification and attribute correctness associated with geometrical shapes, also known as thematic accuracy (ISO, 2002)
Consistency	Logical consistency	Measures internal consistency such as topological correctness and relations of objects
	Semantic accuracy	Measures whether data objects and their meanings are interpreted correctly
Evolution	Temporal quality	Measures validity of changes and rate of updates

Table 3. Quality indicators for VGI

Categories	Specifications	Descriptions
Concrete indicators	Purpose	Predetermined usage of a dataset
	Usage	Application(s) of a dataset
	Lineage	History of a dataset (also known as provenance)
Abstract indicators	Trustworthiness	A subjective judgement based on reliability, trust, reviews and ratings (Flanagin & Metzger, 2008)
	Credibility	A combination of subjective trustworthiness (perception) and objective expertise (accuracy) (Flanagin & Metzger, 2008); a critical example is source credentials in the metadata of VGI. (Frew, 2007; Hovland, Janis, & Kelley, 1953)
	Text content quality	e.g., text length, readability, topical similarity, and the use of technical terminology
	Vagueness	Data ambiguity (e.g., caused by low image resolutions) (De Longueville, Ostländer, & Keskitalo, 2010)
	Local knowledge	Contributors' familiarity of their contributed geographic regions
	Experience	e.g., length of registration and number of features created and edited (Van Exel, Dias, & Fruijtier, 2010)
	Recognition	e.g., acknowledgement (in gamified VGI platform) and peer-review (Van Exel et al., 2010)
	Reputation	e.g., historical mapping accuracy and interaction between collaborators (Van Exel et al., 2010)

1.3 Research objectives

There are four objectives of this research:

1. to examine the reliability of the Canadian OSM data in two different scales;
2. to compare the quality of the Canadian OSM road networks with the quality in other locations;
3. to validate new approaches of intrinsic quality evaluation in VGI;
4. to establish implications of quality control for future VGI project development.

The listed objectives are closely related to each other, with the first objective as the foundation.

1.4 Thesis structure

The thesis is organized into four chapters including this introduction. Chapter 2 provides an extensive review of the quality evaluation process of OSM, followed by a case study of London, Ontario on the assessment of completeness, positional accuracy and attribute accuracy of street networks. Chapter 3 extends the work of the case study to all of Canada to check the possibility of finding generalizations from London compared to a national level. Semantic accuracy and lineage were evaluated in addition to the quality measures listed above, followed by a statistical analysis between OSM accuracy and associated provenance information. Chapter 4 offers a summary of the results, as well as a discussion of the limitations and contributions from the previous two chapters. The final remarks give an outlook on the future research directions, such as methods of VGI quality improvement.

Chapter 2

2 Quality Evaluation of Volunteered Geographic Information: The Case of OpenStreetMap*

2.1 Introduction

Although a large amount of geospatial data and wide range of applications have made GIS very popular, the users are often unaware of the data quality. New elements were added to the discussion of geospatial data quality in the 21st century. The interactivity of the new web technology helped create a large amount of user-generated content (UGC). UGC with location information is referred to as user-generated geospatial content (Coleman, Georgiadou, & Labonte, 2009), crowd-sourced geodata (Barron, Neis, & Zipf, 2014) or volunteered geographic information (VGI) (Goodchild, 2007). More specifically, using location-based services (LBS), GPS-enabled devices and/or aerial photos, VGI users actively upload and share data, and the information can be direct or indirect depending on whether users have local knowledge (Haklay, 2013). The activities of contributing VGI have been termed in different ways as well, including collaborative mapping (Jokar Arsanjani & Vaz, 2015), participatory GIS (Elwood, 2006) and public participation GIS (PPGIS) (W. Lin, 2013).

Researchers are interested in VGI because of its values. The conventional apprehension about commercial or governmental cartographical products is authoritative, comprehensive and accurate. However, Coleman (2013) and Dobson (2013) concluded that these databases are often out-of-date, incomplete, of inconsistent quality, and costly to maintain. Therefore, VGI is studied as a crowd-sourced alternative to "authoritative" datasets. OpenStreetMap (OSM) is one of the VGI applications that allow users to create and edit maps using GPS-enabled devices and/or satellite images. As of July 2016, more than 3.4 billion nodes (data points) have been created by over 2.8 million registered users

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* A version of this chapter appears in *Volunteered Geographic Information and the Future of Geospatial Data* edited by C. Campelo, M. Bertolotto, & P. Corcoran.

(Neis, 2017). This chapter extensively summarizes the quality evaluation process of OSM through literature review and a case study of London, Ontario, with focus on the comparison of different assessment methods and findings.

2.2 Background

The term volunteered geographic information (VGI) was suggested by Goodchild (2007) to represent geospatial data contributed by individuals voluntarily. Since VGI is often the most cost-effective solution, crowd-sourced geodata have been applied in many fields, such as participatory planning and spatial decision making. Moreover, VGI is the only source of geodata in some regions because of security or financial concerns. The area of humanitarian relief and crisis management is the most prominent application of VGI. Ushahidi and the Humanitarian OpenStreetMap Team (HOT) are two platforms that have had a strong presence in disaster management since 2008 and 2009 respectively. Table 4 compares some VGI applications with OSM. Although OSM is not the project with the longest history, it is the oldest mapping project in which the geo-information can be applied in more than one field. The number of “registered members” of OSM is relatively small compared to other specialized applications, but the number of “users” could be a bloated figure and does not represent “active contributors”. Like Wikimapia and Waze, OSM has worldwide coverage. The difference is that OSM allows users to freely alter and redistribute its data, which is accessible through multiple servers in different formats. In contrast, Wikimapia only offers its data through one web application programming interface (API) (Neis & Zielstra, 2014), and Waze does not release data from its platform. Therefore, OSM was chosen to be the data source for this chapter. The following subsections start with a discussion of quality concerns in VGI, introduce OSM in detail and end with a list of the spatial data quality metrics.

Table 4. Comparison of volunteered geographic information (VGI) applications

Attributes	OpenStreet Map	Wikimapia	Waze	Moovit	GasBuddy
Founding year	2004	2006	2008	2012	2000
Specialization	Mapping	Mapping	Navigation	Public transit	Fuel prices
Number of users or registered members (in million)	2.8 (in 2016)	1.9 (in 2013)	50 (in 2013)	20 (in 2014)	35 (n.d.)
Coverage in 2016	World	World	World	600+ cities	United States and Canada
License	ODbL	CC BY-SA	Proprietary	Proprietary	Proprietary
Data downloadable	Yes	Yes	No	No	No

Note. ODbL, Open Database License; CC BY-SA, Creative Commons license Attribution-ShareAlike; data for OpenStreetMap from Neis (2017), for Wikimapia from Neis & Zielstra (2014), for Waze from CBC News (2013), for Moovit from "Moovit Company Overview" (2014), and for GasBuddy from "Advertise with us - Gasbuddy Gas Prices" (n.d.).

2.2.1 Quality issues of volunteered geographic information

Community-based systems, like the review systems on Amazon or Airbnb, could be useful in evaluating the relative and latent values of VGI (Feick & Roche, 2013). Data quality assessment is a more explicit way of determining the value of VGI. Quality issues of VGI are typically centered around inconsistency in terms of coverage and accuracy. For instance, remote areas are usually under-mapped (Coleman, 2013). If volunteers are unfamiliar with the remote areas they map, accuracy might be sacrificed because of volunteers' deficiency in local knowledge (Dobson, 2013). In addition to geometrical objects, VGI's metadata is also incomprehensive and inaccurate (Hashemi & Ali Abbaspour, 2015), which creates difficulties for researchers when verifying the semantic accuracy of VGI. Although the International Organization for Standardization (ISO) has published quality principles for geographic information (ISO, 2002), a new quality assurance schema specifically tailored for VGI is needed because of the limitations mentioned above (Van Exel et al., 2010).

The simplified expression of Linus' Law – "Given enough eyeballs, all bugs are shallow" (Raymond 2001, p. 13) – is often quoted as an underlying theory for discussing the issues of data quality (e.g., Haklay et al. 2010; Miller and Goodchild 2015; Goodchild and Li 2012; Goodchild 2013). It is hypothesized that more contributors usually create more reliable information (Flanagin & Metzger, 2008). However, Linus' Law may not work well in a spatial context (Elwood, Goodchild, & Sui, 2013), and this quotation often misleads readers to conclude that most quality issues will be solved if there are enough testers. The full expression of Linus' Law is that "Given a large enough beta-tester and co-developer base, almost every problem will be characterized quickly and the fix (will be) obvious to someone" (Raymond 2001, p. 13). This expression specifies that the "eyeballs" must include those from co-developers, who are professionally trained to debug the Linux operating system in the context of the Raymond article. However, some VGI projects may be contributed mainly by citizen scientists but not professional cartographers. Moreover, the software "bugs" can be identified during the process of using the software. However, errors on maps cannot be recognized or avoided if the map scale is too small, contributors do not have local knowledge, or accuracy is sufficient for certain map applications (i.e., navigation requires less accuracy than road constructions). Furthermore, the contribution pattern of VGI users signifies the necessity of spatial redundancy (Dobson, 2013). For example, 38% of registered OSM members edited at least once, and only 5% of all actively contributed to the project (Neis & Zipf, 2012). Spatial heterogeneity also prevents the existence of consistent global spatial errors that may be corrected all at once. Thus, Linus' Law may not apply to VGI, which means a large number of volunteers may not be enough to ensure the quality of VGI.

2.2.2 Spatial data quality

Spatial data quality can be evaluated internally or externally (Jokar Arsanjani, Mooney, Zipf, & Schauss, 2015). While internal quality assesses the fitness of data for a particular purpose, external quality describes how well data meet specifications. Examples of the extrinsic quality measures include completeness (C), positional accuracy (PA), attribute accuracy (AA), logistical consistency (LC), semantic accuracy (SA), temporal quality (TQ) and lineage (L) (see Table 2 in Section 1.2).

The intrinsic quality indicators contain standards such as data usage (see Table 3 in Section 1.2), and can be derived completely from source data without the help of reference data (Foody et al., 2015). According to Ali, Schmid, Al-Salman, & Kauppinen (2014), Goodchild & Li (2012) and Senaratne et al. (2016), intrinsic methods can be categorized into four groups: crowd-sourcing revision (data validation by contributors), social approaches (reputation and trustworthiness of individual contributors), geographic consistency (logical and contextual inferences using geographic laws) and data mining (independent database examination without using theories from the previous three groups). The focus of this chapter is the external quality of VGI data. However, it has been recognized that the above criteria only assess absolute data quality, while the actual quality is relative to its fitness-of-use (Feick & Roche, 2013; Van Oort, 2006).

2.2.3 OpenStreetMap

OSM is a crowdsourced online mapping platform, which aims to provide free and editable digital mapping products under a new copyright license (Haklay & Weber, 2008). The project implements the resource description framework (RDF), which uses a triple (resource, property, value) to model information (Manola, Miller, & McBride, 2004). Some drawbacks of the RDF structure contain difficulties of translating RDF triples to object-oriented data, ambiguous numbers of classes, and issues in real-world object identification (Girres & Touya, 2010). Since its initiation in August 2004, OSM has been applied in routing and navigation, cartography improvement, Location Based Services (LBS), and 3D city models (Jokar Arsanjani, Zipf, Mooney, & Helbich, 2015). In 2014, high densities of OSM nodes were found in Europe, North America, Russia, Australia and Brazil, while Africa and Greenland were least mapped (Jokar Arsanjani, Zipf, Mooney, et al., 2015). Overall topological errors and missing information in OSM decreased in Germany during the period of 2007 to 2011, and its data quality is becoming as good as authoritative datasets at least in highly-contributing countries (Neis, Zielstra, & Zipf, 2011). However, the project still has a large number of inactive users and small or lightly edited elements (Ma, Sandberg, & Jiang, 2015). Those contributors outside of major urban centers have made very limited contributions as well (Quinn, 2015). According to Haklay, (2010), Jokar Arsanjani, Zipf, et al. (2015), Mooney & Corcoran

(2014), Neis & Zielstra (2014), Neis, Zielstra, & Zipf (2013), Stein, Kremer, & Schlieder (2015) and Vandecasteele & Devillers (2015), OSM can be described by the following key features:

- **Near real-time updates**: Unlike Google Map Maker, which has a review system for submitted edits, OSM publishes modifications just "a few minutes" after contributors save their changes;
- **Data import from multiple sources**: OSM supports data generated GPS, smartphones, and other mapping hardware. In the early years of the project, GPS-enabled devices were the most popular data generators. This situation was changed because Yahoo! (from 2007 to 2011) and Microsoft Bing (since 2010) agreed to provide their aerial imageries for OSM enthusiasts to trace data. Some countries, such as the United States and Canada, also had volunteers to import authoritative datasets into OSM;
- **Data export in multiple formats**: OSM data can be downloaded at different scales (e.g., continental, regional or metro) in different formats (e.g., OSM Extensible Markup Language (XML), Protocol Buffer Binary Format (PBF) or shape file) from several servers (e.g., Planet OSM, Geofabrik or Mapzen);
- **Different flavours of editors**: The web-based iD editor has a simple user interface for beginners to immerse into geodata contributions. Moreover, Potlatch or JOSM (Java OpenStreetMap Editor) are favoured by advanced mappers. Other editors are available across operating systems and platforms as well;
- **Full edit history**: OSM keeps all historical edits in its full history dump site, but only the latest versions of objects are available in other forms of extracts. Each "changeset" stores all edits of one contributor in one session;
- **Three object types**: The resource in RDF represents the geometric features. A "node" represents a point, while a "way" consists of lines or polygons (closed line features). A "relation" connects related nodes, ways and relations with each other;
- **Tags as metadata**: Attributes of objects are expressed as "key:value" pairs, which match the property and value elements in RDF;

- **Undistinguishable contribution types**: it is not required to attach the information of contribution types in OSM (e.g., from GPS, aerial photo tracing, or data import);
- **Spatial temporal heterogeneity**: Patterns and quality of contributions differ from one place to another, and contributions are neither linear nor predictable because of mapping parties and data import. Although geometric shapes may not change very frequently, tag information may change very quickly;
- **Manifold collaboration channels**: The official OSM wiki provides the knowledge base of the project. Other communication methods include Internet relay chats (IRCs) (OpenStreetMap, 2015b) and mailing lists (OpenStreetMap, 2016a). Community events such as "mapping parties" are organized both online and offline, with the yearly "State of the Map" conference attracting most attendees.

Previous studies have surveyed the patterns of contributors' activities. For instance, most contributions in OSM are isolated without planned collaboration (Mooney & Corcoran, 2012b, 2012c), and the majority of the members have most of their mapping activities within the first three months of their registration (Neis & Zipf, 2012). Roads usually attract a lot of interest first. Other features, like buildings, are added later (Gröchenig, Brunauer, & Rehrl, 2014b; Neis & Zielstra, 2014). Contribution inequality was observed in terms of digital divide, demographic difference, area distribution, and quantity of mapping activities. Developing countries have usually received fewer contributions due to their lack of the latest technology infrastructure (Jokar Arsanjani, Zipf, Mooney, et al., 2015; Sui, Goodchild, & Elwood, 2013). Haklay (2013) also worried about the participation inequality if contributors are mainly well-educated males with high incomes. In fact, over 60% of surveyed OSM contributors were 20 to 40 years old, and a similar ratio applied to those who had a higher education degree (Budhathoki & Haythornthwaite, 2013; Stephens, 2013). Contradicting the widely-accepted speculation, nearly half of the surveyed OSM contributors had educations or work experience in geography, geomatics, urban planning or computer science (Budhathoki, 2010). The earliest contributions were concentrated near university campuses, while farmland and water bodies were mapped last (Jokar Arsanjani, Helbich, Bakillah, & Loos, 2015). There are differences between users, registered members and contributors as well. Over 90% of feature creations and modifications were completed by the top 10% of contributors (Mooney & Corcoran, 2014), and a lot of them map in two or more countries (Neis & Zipf, 2012). Among those serious contributors, "tagging" represents the major action of the group followed by "geometry only" and "creation only" (Mooney & Corcoran, 2014). In recent years, most contributors (72%) were still in Europe with Germany at the top (Neis & Zielstra, 2014; Neis & Zipf, 2012), which explains why OSM is well-developed in most European countries. An activity area for each member can range from one soccer field to more than 50 km^2 (Neis & Zipf, 2012). An analysis of regional mapping history before any plan for using OSM data, because of its known impacts on mapping methods and progress on OSM quality, is recommended (Gröchenig, Brunauer, & Rehrl, 2014a).

2.3 A review of OpenStreetMap quality assessment

An extensive survey of literature (as of July 2016) found 60 articles relevant to quality evaluation of OSM (see Appendix A). Four databases were used in this process including Web of Science, Scopus, Engineering Village (Geobase) and Proquest (dissertations & theses). 334 articles were found initially using keywords "OpenStreetMap AND (quality OR accuracy)" with the option of anywhere except full text, and the number of relevant articles went down to 202 after removing duplicates. A full-text review of the 202 articles identified 39 articles listed in the Appendix. In addition, 21 relevant articles were found based on an examination of the 39 articles' reference sections. Only studies written in English were retained. It is worth to mention that some excluded articles are not totally irrelevant, but they focus more on method assessment instead of quality of specific areas (Basiri et al., 2016; Brovelli, Minghini, Molinari, & Mooney, 2016; Fan, Yang, Zipf, & Rousell, 2015; Graser, Straub, & Dragaschnig, 2014; Gröchenig et al., 2014b; Jokar Arsanjani, Mooney, Helbich, & Zipf, 2015; X. Zhang & Ai, 2015). In Appendix A, time represents the actual time the OSM data was downloaded, which is more accurate than the year of publication. Only years were recorded because of various time precision. Data were retrieved from 2007 to 2014, indicating the discussion of OSM quality assessment started around 2007 and continued as a trending topic until recent times. A limited number of studies were implemented using national data, signifying current exploration stage of OSM quality analysis. Most studies had European regions as their study areas, which was not surprising considering the massive number of European OSM users. Furthermore, most studies used a reference dataset to evaluate the extrinsic quality of OSM data, which include a mix of governmental and commercial databases. For articles that do not have a reference dataset, some constructed frameworks, some analyzed user behavior or data trust, and the rest studied intrinsic quality using data history.

The frequency of examined data quality criteria is shown in Figure 1. Data completeness dominates the quality analysis of OSM, with positional accuracy and attribute accuracy the second and the third most popular criterion. The common evaluation methods of all criteria are explained in the following paragraphs.

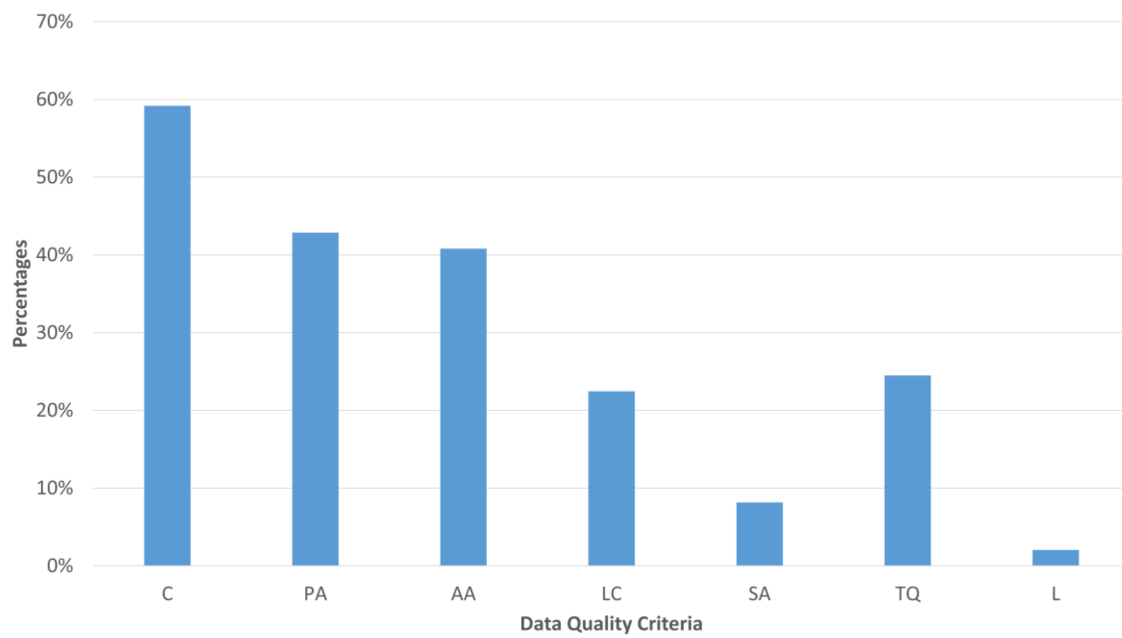

Figure 1. Summary statistics of examined data quality criteria in Appendix A

Generally, there are two types of methods to measure data completeness: unit-based and object-based (Table 5). The concept behind unit-based methods is to compare total length, area, or number of objects in OSM with those in a reference dataset. Many studies have used this method because of its easiness of implementation. Hochmair et al.

(2015) specially considered street network density and visually compared bike lanes with Google street view to avoid potential mistakes. On the other hand, (automated) feature matching is involved in object-based methods using attributes or geometric properties. For example, street segments have orientation and length, and building footprints can be matched by their centroids or overlap ratio between OSM data and a reference. It is worth mentioning that the completeness of land use may be calculated without a reference, since a 100% result means everywhere is covered by a land use feature (Jokar Arsanjani, Mooney, Zipf, et al., 2015).

Table 5. Methods of measuring completeness

<table>
<tr><th>Types</th><th>Criteria</th><th>Examples</th></tr>
<tr><td rowspan="4">Unit-based</td><td>Number of objects (e.g., attributes, POIs or buildings)</td><td rowspan="2">Barron, Neis, & Zipf (2014),
Fan, Zipf, Fu, & Neis (2014),
Girres & Touya (2010),
Haklay (2010),
Hecht, Kunze, & Hahmann (2013),
Hochmair, Zielstra, & Neis (2015),
Jackson et al., (2013),
Jokar Arsanjani, Barron, Bakillah, & Helbich (2013),
Jokar Arsanjani, Mooney, Zipf, & Schauss (2015),
Jokar Arsanjani & Vaz (2015),
Mashhadi, Quattrone, & Capra (2015),
Neis, Zielstra, & Zipf (2011),
Zielstra & Zipf (2010)</td></tr>
<tr><td>Total length or area</td></tr>
<tr><td>Density</td><td rowspan="2">Hochmair et al. (2015)</td></tr>
<tr><td>Visual comparison</td></tr>
<tr><td rowspan="4">Object-based</td><td>Centroids</td><td rowspan="2">Hecht et al. (2013)</td></tr>
<tr><td>Overlap ratio</td></tr>
<tr><td>Attribute match (e.g., name)</td><td rowspan="2">Jackson et al. (2013),
Kalantari & La (2015),
Koukoletsos, Haklay, & Ellul (2012),
Ludwig, Voss, & Krause-traudes (2011)</td></tr>
<tr><td>Geometric match (e.g., distance, orientation, length)</td></tr>
</table>

The methods of measuring positional accuracy are categorized by data types (Table 6). A common method for points of interest is Euclidean distance, while buffer analysis is popular for line segments. A buffer of width “x” is created around a road segment from an authoritative dataset, and the percentage of the corresponding OSM road segment that falls within the buffer is calculated (Goodchild & Hunter, 1997). The buffer size differs from one study to another, indicating that there is no theory behind this method. The positional accuracy of the reference datasets is the key of buffer size determination. In terms of polygon features, centroids, corner points and surface are considered for distance measurement.

Table 6. Methods of measuring positional accuracy

Data Types	Methods	Examples
Point	Euclidean distance	Girres & Touya (2010)
		Amelunxen (2010)
		Jackson et al. (2013)
Line	Compare actual road conjunction with previous locations	Barron, Neis, & Zipf (2014)
	Hausdorff distance	Girres & Touya (2010)
	Average distance (McMaster, 1986)	
	Buffer analysis (Goodchild & Hunter, 1997; Hunter, 1999)	Haklay (2010), Jokar Arsanjani, Barron, Bakillah, & Helbich (2013), Ludwig, Voss, & Krause-traudes (2011)
	Bidimentional regression (Friedman & Kohler, 2003; Tobler, 1994)	Helbich, Amelunxen, & Neis (2012)
	G*-statistics (Getis & Ord, 1992)	
Polygon	Surface distance (Vauglin, 1997)	Girres & Touya (2010)
	Average distance of corresponding (corner) points	Fan, Zipf, Fu, & Neis (2014)
	Distance between centroids	Kalantari & La (2015)

The methods of measuring attribute accuracy have four types of usages (Table 7). First, presence of OSM tags (e.g., oneway flags of street segments) can be looked up through examining each geometric object. Second, similarities of strings can be calculated by different algorithms. For example, the Levenshtein distance is the number of deletions, insertions, or reversals required to transform one string to another. The algorithm was originally developed to tackle the issue of binary information transmission (Levenshtein, 1966). The larger the Levenshtein distance, the greater the differences between strings. Third, numbers can be subtracted, and the absolute values of the results can reflect the differences between them. Finally, thematic accuracy (e.g., for land use accuracy assessment) can be measured by confusion matrix and kappa index.

Table 7. Methods of measuring attribute accuracy

Usages	Criteria	Examples
Measures attribute completeness	Tag presence	Girres & Touya, (2010), Ludwig et al. (2011)
Compares strings (text)	Levenshtein distance (Levenshtein, 1966)	Girres & Touya (2010)
	Similarity ratio (calculated by difflib in Python)	Kalantari & La (2015)
Compares numbers	Difference in speed limits	Ludwig et al. (2011)
Measures thematic accuracy	Classification accuracy by confusion matrix	Estima & Painho (2013), Jokar Arsanjani, Helbich, Bakillah, Hagenauer, & Zipf (2013), Jokar Arsanjani, Mooney, et al. (2015), Jokar Arsanjani & Vaz (2015)
	Kappa index	

A framework was constructed exclusively for logical consistency (Hashemi & Ali Abbaspour, 2015). Spatial scenes – sets of spatial objects with spatial relations – are compared in this framework. Topology, distance and direction are some examples of useful spatial relations (Hashemi & Ali Abbaspour, 2015). Here, topology is “the study of qualitative properties that are invariant under distortion of geometric space” (e.g., the London underground map) (Jiang, 2013, p. 128). For instance, two articles from Appendix A studied logical consistency of street networks considering topological errors (e.g., connectivity of roads and structure of network), turn restrictions and inter-theme consistency (Girres & Touya, 2010; Neis et al., 2011). Another two articles examined logical consistency of polygons, both using shape similarity ratio in additional to other methods such as turning function distance, number of vertices, mean vertex spacing distance, and feature areas (Fan et al., 2014; Kalantari & La, 2015). Although OSM has a dedicated webpage to record known data errors (OpenStreetMap, 2016c), Girres & Touya (2010) mentioned that integrity constraints are not enforced to ensure logical consistency in OSM.

Methods of other data quality criteria are summarized below. Only four out of the 60 articles analyzed semantic accuracy, and two of them compared attributes for the assessment (Girres & Touya, 2010; Jokar Arsanjani, Barron, et al., 2013). Fan et al. (2014) did something special to identify the n:m relations of building footprints between OSM data and a reference dataset. Temporal quality was generally evaluated as a spatial-temporal analysis with the rate of changes over time. Level of details (LOD) assessment can be divided into five schemas including conceptual schema, geometric resolution, semantic resolution, geometric precision and granularity (the size of the minimal features) (Touya & Reimer, 2015). Finally, a number of collected studies analyzed relations between user behaviors or data trust to user information and/or edit history.

Mixed results were found across different locations, times, data types and criteria. Some urban areas with high population density had similar or even better quality than some reference datasets. However, rural areas received less attentions and had scarce coverage. Overall, the findings of collected articles follow the two classical geographic theories: Tobler's (1970) first law of geography – near things are more related than others – and the second law of geography – geographic phenomena vary across the globe (spatial heterogeneity) (Goodchild, 2009).

2.4 Case study

According to Appendix A, only a small number of articles evaluated the quality of the Canadian OSM data (e.g., Meier, 2015; Tenney, 2014). Although Tenney (2014) performed a national study, the results were still preliminary. Thus, there is a need to further evaluate the Canadian OSM quality. The study area here is the Census Metropolitan Area (CMA) of London, Ontario, Canada (see Figure 2). London is the eleventh largest CMA in Canada with more than 474,000 inhabitants, including two cities (London and St. Thomas), two municipalities (Thames Centre and Central Elgin) and four townships (Strathroy-Caradoc, Middlesex Centre, Southwold and Adelaide-Metcalfe) (Statistics Canada, 2012). The rate of economic growth in the region was moderate in recent years because of an improved manufacturing sector and a stronger housing market. Two datasets, the source and the reference data, are required for this evaluation. The source data are the 2016 OSM metro extracts of London, Ontario from Mapzen[9] in the imposm shapefile format[10]. The reference data are the 2015 DMTI road networks from Scholars Geoportal[11], which has a positional accuracy ranging from 0.6 (urban) to 30 m (rural) (DMTI Spatial Inc., 2015). It is therefore hypothesized that urban roads have higher positional accuracy in OSM as well. The governmental datasets, such as the 2015 National Road Network (NRN) data from Natural Resources Canada and the London street centrelines collected by the City of London, were not chosen as the reference dataset because a commercial dataset is preferred when available (Haklay, 2010). Positional accuracy is not specified in both datasets as well (e.g., only indicated "in meters" from NRN) (Natural Resources Canada, 2015). In terms of the municipal dataset which only covers the City of London but not the CMA, a divided road is presented by one centreline, which differs from the representation in OSM.

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9 https://mapzen.com/data/metro-extracts/

10 https://mapzen.com/documentation/metro-extracts/overview/#choose-a-file-format

11 http://geo2.scholarsportal.info/

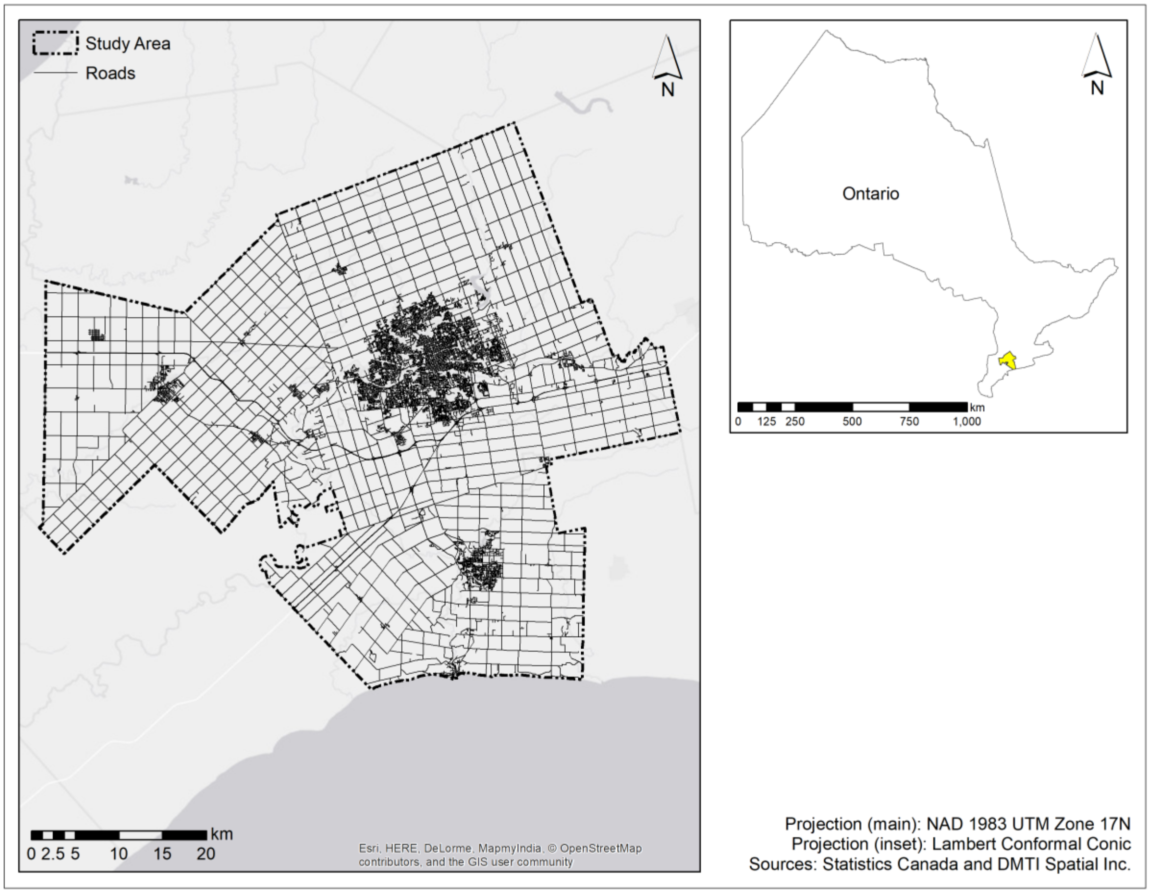

Figure 2. Study area of the case study

2.4.1 Methods

The OSM quality, specifically completeness, positional accuracy and attribute accuracy, was assessed using the following techniques and ArcGIS tools (see Figure 3 and 4). The attributes were first processed and matched based on Table 8. Evaluation results were classified according to the new road ranks in Table 9. Geometric feature matching was performed before evaluating the positional and attribute accuracy. The unmatched road segments were identified using the "Detect feature changes" tool in ArcGIS with a search distance of 30 m (the maximum positional offset of the DMTI data) and removed afterwards. The lengths and densities of roads were calculated to analyze the data completeness. This unit-based method was chosen because it is easy to implement and has been used in many previous studies (see Table 5). Next, the buffer analysis was used to assess the positional accuracy. This method was validated in the first OSM quality assessment (Haklay, 2010) and other studies (see Table 6). Using a self-developed python script and the arcpy library, buffers with widths of 1 to 10 m were created around the DMTI street networks, and the matched OSM road segments that fell within the buffers were clipped for calculating their proportions to the total OSM road length (see Figure 5, adapted from Goodchild & Hunter, 1997). Finally, the attribute accuracy was evaluated by tag presence, number difference and Levenshtein distance. Tag presence measured whether an OSM road attribute was present if a DMTI road attribute was provided. The absolute difference between two numeric fields were calculated as follows: $d = |x - y|$. Levenshtein distance (see Section 2.3) of two text fields was computed using a dynamic programming python script (Levenshtein, 1966).

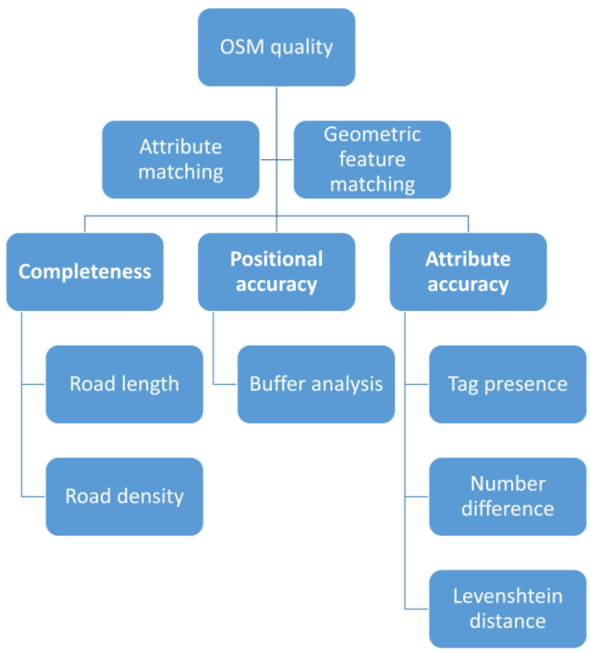

Figure 3. Methods of the case study

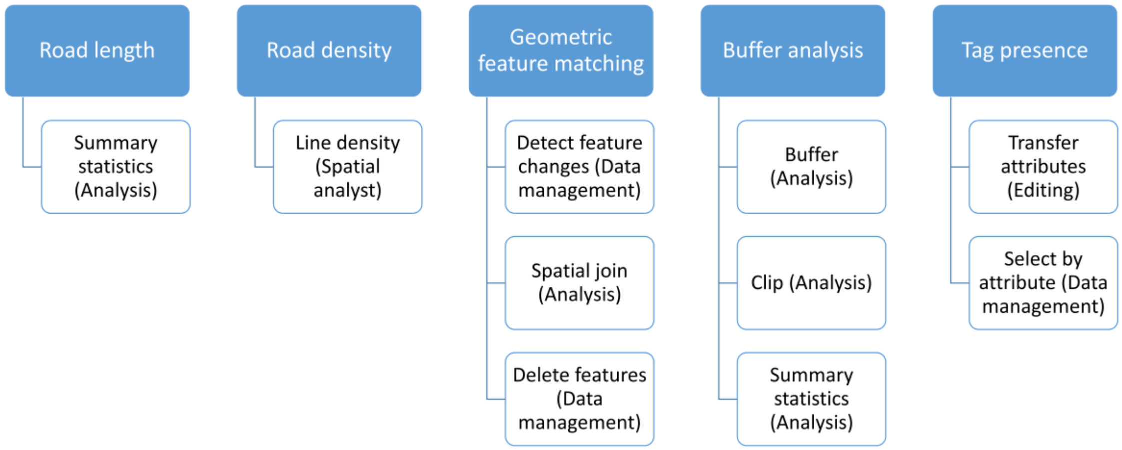

Figure 4. ArcGIS tools used in the case study

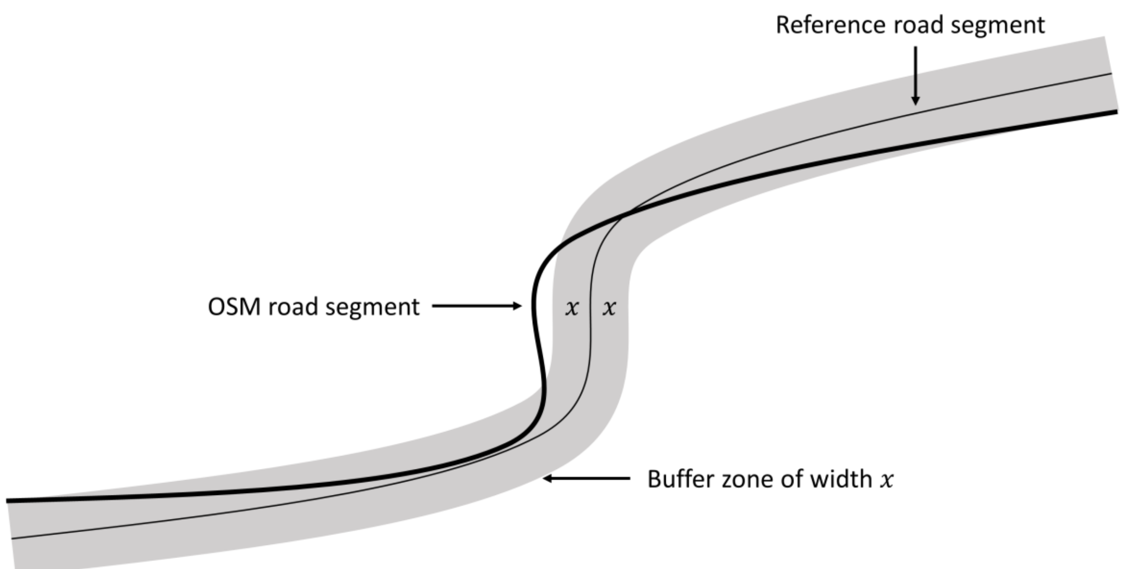

Figure 5. Example of the buffer analysis

Table 8. Matches of attributes

Field Name	Field Type	Field Description
name	Text	Full street name
length	Number	Length of the road segment
rank	Number	New road classifications
UID	Number	Unique ID
preDir	Text	Prefix direction
preType	Text	Prefix street type
stName	Text	Street name component
sufType	Text	Suffix street type
sufDir	Text	Suffix direction
tunnel	Number	1 = tunnel; 0 = not tunnel
bridge	Number	1 = bridge; 0 = not bridge
oneway	Number	1 = oneway; 0 = two ways; -1 = incorrect input

Table 9. Matches of road classifications

New Rank	DMTI Road Types	OSM Road Types	
0	N.A.	Unclassified	
1	Expressways	Motorway	Motorway_Link
2	Primary Highways	Trunk	Trunk_Link
3	Secondary Highways	Primary	Primary_Link
4	Major Roads	Secondary	Secondary_Link
5	Local Roads	Tertiary	Tertiary_Link
		Residential	Service
6	Trails	Footway	Steps
	Proposed Roads	Path	Track
		Raceway	Cycleway

2.4.2 Results and discussion

2.4.2.1 Completeness

Figure 6 shows the road lengths by ranks. Many of the ranks have close lengths except rank 0, 5 and 6. Visual examination confirmed that most unclassified (rank 0) road segments of OSM are local roads (rank 5) in suburban areas. Thus, the length difference of rank 5 is actually minimal if the length of rank 0 is added. The difference of rank 6 is large enough to influence the total road length because of the large number of footways in the OSM data. This is also the case of the United States (as of 2012) (Zielstra, Hochmair, & Neis, 2013) and Germany (as of 2011) (Neis et al., 2011). If rank 6 is excluded, the difference is significantly reduced. However, OSM has a longer total length than DMTI with or without rank 6, which is different from previous studies in which the total length of OSM motorways was still shorter than reference datasets (Neis et al., 2011; Zielstra et al., 2013). The better data completeness potentially benefits from data import and the increased number of contributors over the years.

The road densities of the two datasets is displayed in Figure 7. In general, urban areas especially the City of London and the City of St. Thomas have higher road density, which potentially helps to generate shorter and better routes in navigation applications (Mondzech & Sester, 2011). The location of dense areas verifies that areas with denser population tend to have higher contributions (Jokar Arsanjani & Bakillah, 2015). The maximum density of DMTI is about one-third of that in OSM. The difference is reflected in urban areas, and the significant disparity of footways (rank 6) should have great influence on the road density as well.

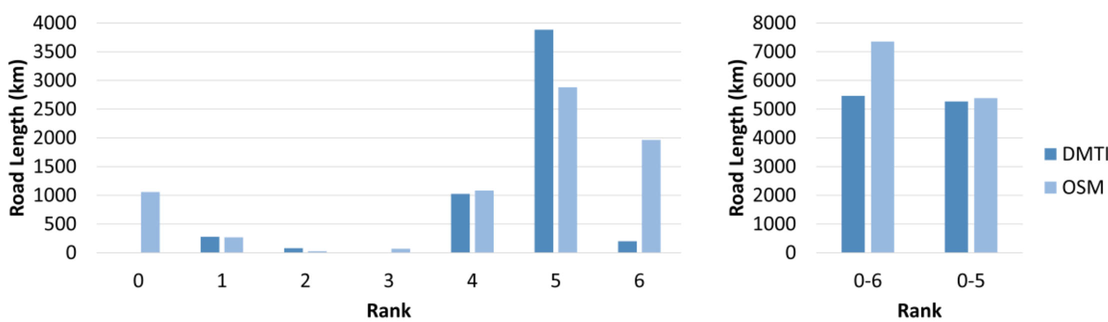

Figure 6. Classified road lengths in London, Ontario

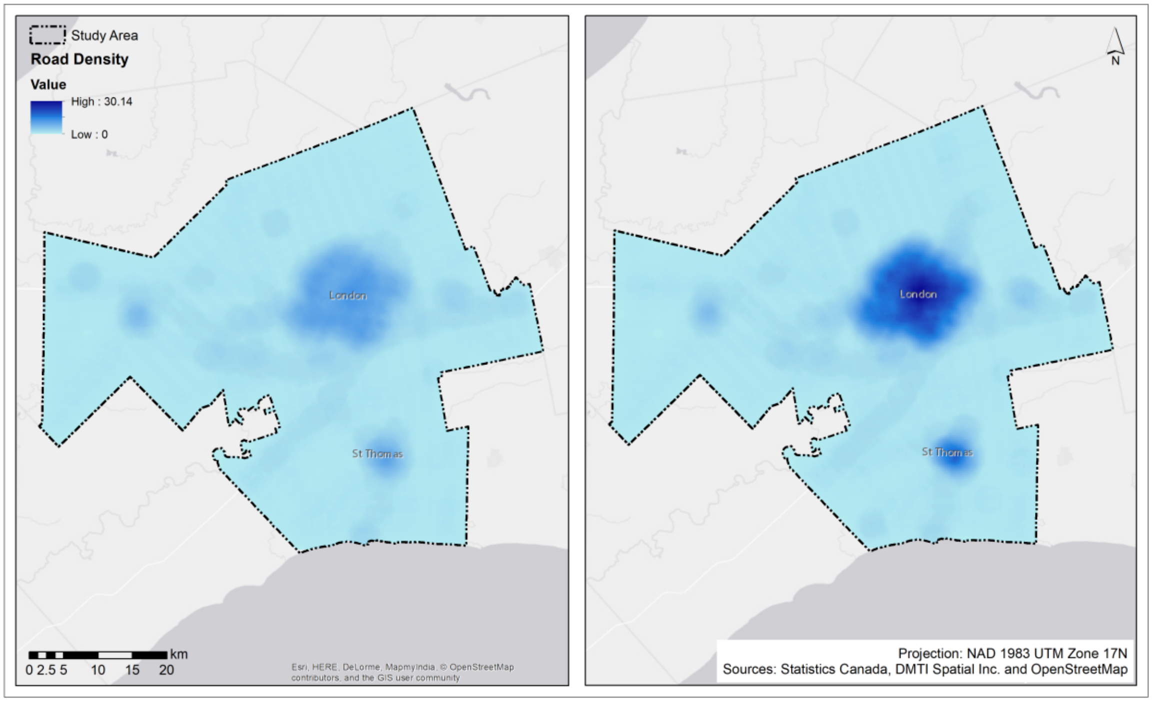

Figure 7. Road density (m/km^2) in London, Ontario

2.4.2.2 Positional accuracy

To improve the results of the geometric feature matching, rank 6 is excluded from the following analysis. Figure 8 shows the proportions of OSM road segments that fall within the buffers of DMTI road segments with a range from 1 to 10 m. Approximately all ranks of roads have a logarithmic increase of their positional accuracy. The average positional offset is 2.3 m, which is significantly better than the results in London, UK and England in 2007 (5.8 m) (Haklay, 2010) and 2009 (7.9 m) (Antoniou, 2011). At buffer size of 1 m, the positional accuracy ranges from 14.9 to 59.6%. The accuracy increases at a relatively fast rate until 6 m. After that, the accuracy starts to only increase gently. Over 86% of road segments have positional errors within 5 m, which is also better than 73% of road segments in Germany in 2009 (Ludwig et al., 2011). At buffer size of 10 m, most ranks have over 91% of positional accuracy except rank 2 and 3. However, the lengths of roads in these two ranks are relatively short (See Figure 6), which means their results may not be representative. The most accurate rank at the 10-m buffer is rank 0 (local roads in suburban areas).

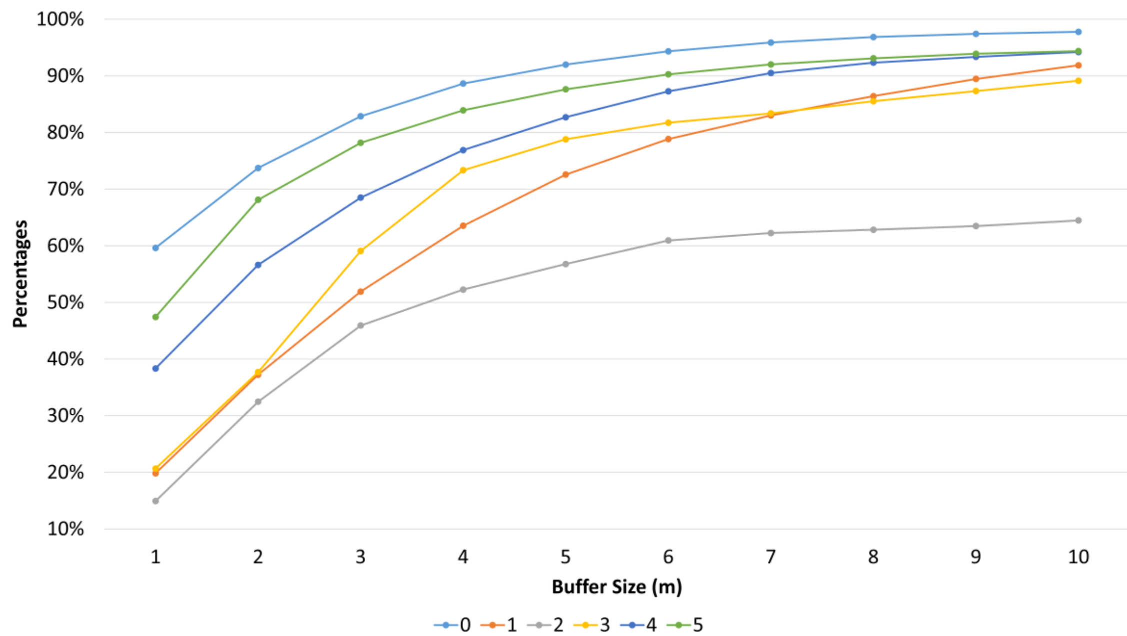

Figure 8. Trends of the OSM positional accuracy in London, Ontario

2.4.2.3 Attribute accuracy

The percentages of attribute accuracy are calculated by road lengths as well. Table 10 lists the proportions of presented OSM tags against the available DMTI attributes. The numeric fields are not included since all OSM road segments have a rank (rank 0 = unclassified) and the remainders have limited number of entries. The presence rates are mostly very high except for sufDir (e.g., N, S, W, E), which probably indicates that the suffix directions are not the primary concerns to the OSM users or not well-known to the OSM contributors. The presence rate of rank 1 under sufType is extremely low as well, and the reason is that a large number of highway segments miss the suffix type “RAMP”. The overall presence rate of sufType is not affected because of the relatively short length of highway. The attribute completeness of London, Ontario are actually superior comparing to French streets (85% for types and 43% for names) (Girres & Touya, 2010) and German streets (82.5% to 94.4% for names) (Ludwig et al., 2011) in 2009.

Table 10. Tag presence in London, Ontario

OSM Rank	Percent	OSM Rank	Percent
preDir		sufType	
4	100.0%	0	99.5%
5	91.6%	1	27.9%
Overall	93.2%	2	92.8%
preType		3	79.0%
1	99.7%	4	98.5%
3	94.1%	5	97.2%
Overall	99.5%	Overall	96.8%
stName		sufDir	
0	99.6%	0	0.0%
1	97.7%	1	42.0%
2	100.0%	4	69.3%
3	100.0%	5	46.8%
4	99.5%	-	-
5	97.4%	-	-
Overall	98.4%	Overall	62.1%

Table 11 presents the absolute difference of the numeric attributes between the OSM and DMTI data. Only 70.6% of the OSM road segments have matched road classifications, which is largely due to the unclassified local roads in suburban area (the 21.1% with a difference of 5). The rest of the fields have almost perfect accuracy; however, the results need to be interpreted with caution because of the short total length of tunnels, bridges and oneway roads. Still, the nearly 98% of oneway flag accuracy in London, Canada is better than the 16% completeness in France in 2009 (Girres & Touya, 2010).

Table 11. Number differences in London, Ontario

Difference	Percent	Difference	Percent
rank		bridge	
0	70.6%	0	99.5%
1	7.1%	1	0.5%
2	0.9%	oneway	
3	0.0%	0	97.9%
4	0.2%	1	2.1%
5	21.1%	2	0.0%
tunnel		-	-
0	100.0%	-	-
1	0.0%	-	-

Table 12 lists the Levenshtein distance of the text fields. Overall, the longer the field content, the larger the Levenshtein distance. Therefore, preDir and sufDir have excellent accuracy since the length of these fields is one letter. Another reason of the nearly perfect accuracy of preDir is due to its small number of entries, and so does preType. The accuracy results of stName and sufType are lower than the others, but still above 85%. A Levenshtein distance of 1 to 3 usually represents spelling mistakes (Girres & Touya, 2010). However, a small portion of stName and sufType have large Levenshtein distance that is greater than 3. The large Levenshtein distances do not affect the overall accuracy as the average Levenshtein distance of stName is only 0.8, which is significantly smaller than the same variable (4.96) of lake names in France in 2009 (Girres & Touya, 2010).

Table 12. Levenshtein distances (LD) in London, Ontario

LD	Percent	LD	Percent
preDir		sufDir	
0	99.7%	0	97.3%
1	0.3%	1	2.7%
preType		sufType	
0	99.4%	0	89.2%
3	0.6%	1	0.0%
stName		2	4.6%
0	86.1%	3	2.2%
1 to 3	3.1%	4	3.8%
> 3	10.9%	5	0.2%

2.5 Conclusions

Although OSM has better data completeness and overall good positional and attribute accuracy comparing to DMTI, it still has some quality issues. For example, the majority of local roads in rural areas remain unclassified. Misspelling of street names and suffix types still exists, and a large number of suffix directions are missing as well. Still, the general OSM quality of London, Canada in 2016 has greatly improved comparing to previous studies of the United States and European regions. An interesting finding is that the local roads in rural areas (rank 0) actually have the highest level of positional accuracy, which contradicts the assumption brought up at the beginning of Section 2.4. This high accuracy of local roads in rural areas is perhaps due to the data import from an old version of NRN starting in 2008 (OpenStreetMap, 2015a) and the limited user-editing afterwards. Hence, it is worth to explore the OSM quality in a larger area. For instance, there are no reference roads classified as secondary highways (rank 3) in the London CMA, which will not be a problem once the study area is expanded to the national level. In addition, an exploration is still needed for evaluating the trail data (rank 6) if a reference dataset is available. Other future research questions pertaining to OSM and VGI are as follows:

- Which data source, the commercial organization, the governmental data bureau or VGI, should be used under which circumstances?
- Are there better and more efficient methods to evaluate the extrinsic (when a reference dataset is available) and intrinsic (e.g., data history analysis) OSM quality?
- How can one accurately automate the quality assessment process?
- How can one improve OSM quality in general?

Chapter 3

3 Accuracy and Provenance Evaluation of the Canadian OpenStreetMap Data*

3.1 Introduction

The advancement and availability of technology such as Web 2.0, the Global Positioning System (GPS) and high-speed internet has resulted in the proliferation of geospatial data in the 21st century. Users are no longer limited to browsing but also creating contents online, and geographers are particularly interested in user-generated geospatial content (Coleman et al., 2009). Different concepts have been defined to describe this worldwide phenomenon, namely volunteered geographic information (VGI) (Goodchild, 2007), crowd-sourced geodata (Barron et al., 2014), public participation GIS (Sieber, 2006), collaborative GIS (Balram & Dragicevic, 2008), participatory GIS (Elwood, 2006), and community integrated GIS (Elmes et al., 2005). Compared to other concepts, VGI targets end-users, who are usually laypeople with their own needs and motivations (Flanagin & Metzger, 2008). The nature of VGI has led to the widely-discussed concern of its data quality. Especially with the availability of satellite images, more and more contributors have become "armchair mappers" who only trace objects from aerial photos without local knowledge or without making measurements with GPS devices (Neis et al., 2013). Although more detailed studies are needed, "armchair mapping" (or remote mapping) may cause various quality issues because of language barriers, limited image resolutions, lack of cartographic skills and loosely enforced specifications.

OpenStreetMap (OSM) is one of the initial and long-lasting VGI mapping projects that aims to develop a free and accessible world map. Established in 2004, OSM has grown quickly in recent years, with the total number of registered users passing 3.5 million in March 2017 (Neis, 2017). The project utilizes the Open Database License

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* A version of this chapter has been submitted to the *International Journal of Digital Earth*.

(ODbL) from Open Data Commons (OpenStreetMap, 2016b), which allows data to be freely accessed from multiple servers (e.g., Planet OSM, Geofabrik or Mapzen) in different formats (e.g., OSM Extensible Markup Language (XML), Protocol Buffer Binary Format (PBF) or shapefile). Tags are stored as "key:value" pairs, which are displayed as attributes associated with map features. Nodes, ways and relations construct the OSM project together, where ways are made of multiple nodes (points), and relations consist of at least one tag with an ordered list of nodes, ways and/or relations (Keßler, Trame, & Kauppinen, 2011). Applications based on OSM are very diverse, and include but are not limited to navigation (e.g., for driving, biking or walking[12]), cartography for specific purposes (e.g., for wheelchair users[13], humanitarian relief[14] and land use/land cover mapping (e.g., Jokar Arsanjani et al. 2015)) and 3D city models (e.g., Over et al. 2010) (OpenStreetMap, 2017b).

Both extrinsic and intrinsic metrics can evaluate spatial data quality. While extrinsic assessment compares OSM data to an authoritative reference dataset using quality measures derived from the ISO standards, intrinsic assessment measures OSM quality through proxies that are known as quality indicators (Antoniou & Skopeliti, 2015). Examples of quality measures include completeness, positional accuracy, attribute accuracy and semantic accuracy (Van Oort, 2006). Provenance (also known as lineage, which can be a quality measure in some cases), that is metadata about an object's source and historical evolution (Bose & Frew, 2005), and trustworthiness, that is a user's subjective judgement (based on ratings or reviews, for example) (Flanagin & Metzger, 2008), are two related quality indicators. Gil and Artz (2007) found that provenance is a major factor that affects users' perceptions of trust in web content, and it is hypothesized that provenance information is associated with trustworthiness of OSM data, which reflects human perceptions of OSM quality (Keßler, Theodore, & Groot, 2013).

[12] http://www.openrouteservice.org/
[13] https://wheelmap.org/
[14] https://www.hotosm.org/

H. Zhang and Malczewski (2017) performed an extensive review of quality evaluation on OSM and found 60 relevant articles as of July 2016. OSM data used in those articles were accessed starting from 2007, which matches the founding year of the notion of VGI (Goodchild, 2007). Most reviewed articles used quality measures to compare OSM data with governmental or commercial datasets in selected European regions (H. Zhang & Malczewski, 2017). Haklay (2010) first examined the completeness and positional accuracy of OSM streets in London and other parts of England in 2007. Compared to the Meridian 2 data from Ordnance Survey, the average positional accuracy was approximately 6 m, and the coverage was about 29% of the area of England (Haklay, 2010). Girres and Touya (2010) extended Haklay's work by comparing the 2009 French OSM data with BD TOPO. Not only did they examine points and polygons in addition to polylines (street networks), Girres and Touya (2010) systematically examined all extrinsic quality measures, including completeness, positional accuracy, attribute accuracy, logical consistency, semantic accuracy, temporal quality and lineage. While the study areas and data types vary from one measure to another, the results of the French study provide confidence for future research on OSM quality. The number of contributors were linearly correlated with the number of tags, the mean version and the mean capture date (Girres & Touya, 2010). The more contributors, the better the attribute accuracy, temporal quality and completeness of the objects. However, in terms of semantic accuracy, OSM specifications were found to be very detailed but did not match with commonly accepted road classification (Girres & Touya, 2010).

Only seven of the 60 studies were implemented nationally, indicating potential difficulties of small scale OSM quality analysis (H. Zhang & Malczewski, 2017). Among those, Zielstra and Zipf (2010) probably performed the first national OSM quality study of streets in Germany. Using the OSM data from 2009, they found that although the total road length of OSM did not catch up with the data from TeleAtlas and Multinet, the number of roads increased very quickly (Zielstra & Zipf, 2010). City centers received more contributions than rural areas, and spatial heterogeneity was observed in terms of completeness (Zielstra & Zipf, 2010). Ludwig, Voss, and Krause-traudes (2011) further examined the positional accuracy and attribute accuracy of streets in Germany using Navteq data. Similar to what Zielstra and Zipf discovered in 2010, populated regions had better attribute accuracy and completess than uninhabited regions (Ludwig et al., 2011). Overall, 73% of the OSM streets in Germany were within a 5 m buffer of Navteq streets in 2009, with 21% in a 5 to 10 m buffer and 6% from 10 to 30 m away (Ludwig et al., 2011). Neis, Zielstra, and Zipf (2011) examined logical consistency and temporal quality of OSM streets in Germany in addition to completeness. Both Ludwig, Voss, and Krause-traudes (2011) and Neis, Zielstra, and Zipf (2011) found that walkways were much more comprehensive than motorways. In rural Germany, OSM could produce better routes of pedestrian navigation than TomTom, while TomTom generally outperformed OSM in car navigation because of reasons such as the lack of turn restrictions in OSM (Neis et al., 2011). One positive finding was that the topological and completeness errors decreased over the years from 2007 to 2011 (Neis et al., 2011). Pourabdollah et al. (2013) studied the attribute accuracy of OSM streets in the United Kingdom using VectorMap District (VMD) data from Ordnance Survey as a reference, and found the difference in urban and rural quality in the U.K. was more complex than previously identified in Germany. Dense areas had the best attribute accuracy, and the middle to large sized cities had the worst quality, leaving less populated areas in the middle (Pourabdollah et al., 2013).

Few studies have focused on North America, primarily because of the less comprehensive data compared to European countries in the first number of years of the OSM project. Contributors tried to improve the regional maps through importing data from available authoritative data sources. Zielstra, Hochmair, and Neis (2013) compared the OSM streets in the United States between 2006 and 2012 to TIGER/Line data from the U.S. Census Bureau, which was fully imported to OSM in 2007 and 2008. Although the import action dramatically increased the completeness of street networks in OSM, especially in sparsely populated areas, the import often resulted in systematic errors in the project and a decreased number of activities in the local mapping community (Gröchenig et al., 2014a; OpenStreetMap, 2017a; Zielstra et al., 2013). For example, as pointed out by Girres and Touya (2010), OSM does not share the same road classification system with other databases such as TIGER/Line, which led to either incorrectly classified or unclassified roads in the U.S. Previously linked walkways and motorways may have been disconnected due to the import as well (Zielstra et al., 2013). Therefore, OSM quality is generally difficult to evaluate and predict because of data import (Zielstra et al., 2013). In

Canada, Tenney (2014) performed an OSM street quality analysis without providing detailed results. Similar to the U.S., attention should be paid in Canada to the impacts of data import (OpenStreetMap, 2015a) and associated systematic error propagation (Tenney, 2014).

Intrinsic quality assessment was explored in the following studies. Haklay et al. (2010) examined the validity of Linus' Law (see Section 2.2.1) on the positional accuracy of OSM streets in London, England in 2007. Although the relationship was not linear, Haklay et al. (2010) found some evidence to support the hypothesis that more contributors led to higher positional accuracy. Keßler, Theodore, and Groot (2013) used a field survey of attribute accuracy, logical consistency and completeness in Münster, Germany in 2011 to evaluate trust as proxies for OSM quality. Five trust-related parameters, containing versions, (number of) users, confirmations (revisions made in the neighbourhood of a feature after the last modification of a feature), tag corrections, and rollbacks (of tags), were derived from the OSM full history dump[15] (Keßler et al., 2013). A moderate positive correlation was found between trust-related parameters and data quality (Keßler et al., 2013). Barron, Neis, and Zipf (2014) proposed a comprehensive framework of fitness for purpose for OSM quality assessment. Six subareas of OSM applications were identified, including general information on the study area, routing and navigation, geocoding, points of interest search, map applications, and user information and behaviour (Barron et al., 2014). Jokar Arsanjani and Bakillah (2015) applied a logistic regression model to explore the potential impacts of socio-economic variables on OSM contributions in Baden-Württemberg state, Germany in 2013. Variables such as high population density and high income were identified to be related to higher OSM contributions (Jokar Arsanjani & Bakillah, 2015). However, using both spatial and non-spatial techniques, Mullen et al. (2015) failed to verify the assumption that certain demographic properties are associated with positional accuracy and completeness of OSM schools in Denver, U.S. in 2011.

[15] https://planet.openstreetmap.org/planet/full-history/

The main objective of this study is to assess the extrinsic quality of OSM street networks in Canada and evaluate the feasibility of intrinsic quality assessment using OSM metadata. Completeness, positional accuracy, attribute accuracy and semantic accuracy were chosen as the quality measures. It is presumed that there is a relationship between selected quality measures and quality indicators, namely version, source and last modified date. Statistical analysis was implemented to check the existence of any associated relations and/or patterns.

3.2 Data and methods

This research focuses on the quality of OSM in Canada. To the best of the authors' knowledge, previous studies have not covered the Canadian OSM quality in detail. Two databases were compared to evaluate the extrinsic OSM quality. The reference data were the DMTI road networks published on Sept. 1, 2015, of which the positional accuracy is less than or equal to 30 m (DMTI Spatial Inc., 2015). The OSM data were extracted from the full history dump and then processed using open-sourced packages on a Linux server (see Figure 9). Using the Osmium Tool, time filter was first applied to retrieve the global OSM data on the last modified date of the reference data. The Canadian data were then clipped using the OSM History Splitter. Finally, street networks in Canada were loaded from PBF to the PostgreSQL database combining exports from Imposm 3 and Osmosis.

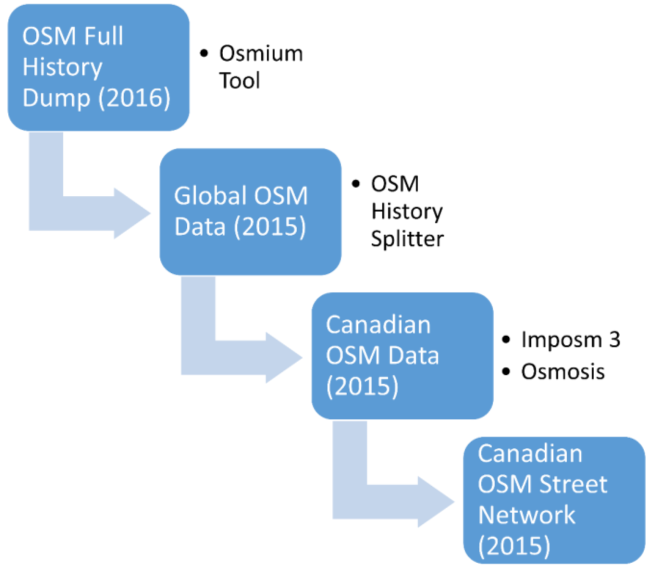

Figure 9. OSM data extraction

Quality measures were analyzed by the following methods (see Figure 10). Attribute and geometric feature matching was implemented first based on Section 2.4.1. Completeness was evaluated by total road length and road density. This unit-based approach was widely used in previous studies (e.g., Haklay 2010; Girres and Touya 2010; Zielstra and Zipf 2010). Buffer analysis was employed to measure the positional accuracy (Goodchild & Hunter, 1997). Buffers of widths from 5 to 30 m, with a 5-m interval, were generated around the reference street networks, and the percentages of OSM roads that fell within the buffers were computed. In terms of attribute accuracy, tag presence reflects the completeness of road attributes through summarizing the number of non-empty OSM tags, and Levenshtein distance (Levenshtein, 1966) represents the steps required to transform one string to another. All OSM street name components (prefix and suffix directions and street types) except core street names were cleaned, capitalized, and transformed to abbreviated forms (e.g., BLVD for Boulevard) to match the format in DMTI. The absolute differences of numeric attributes, such as road classification, were calculated to check semantic accuracy (Girres & Touya, 2010). Provenance attributes, including version and last modified date, were collected for the statistical analysis as the next step. Source information was filtered individually to figure out the impacts of data import on Canadian OSM quality.

Both spatial and non-spatial techniques were applied to explore the potential relationship between OSM accuracy and provenance. With regards to the non-spatial approaches, scatter plots were first created for exploratory analysis. An ordinary least squares (OLS) linear regression model (Burt, Barber, & Rigby, 2009) was later applied to search the possible global correlation between quality measures and indicators. In terms of the spatial techniques, Moran's I (Moran, 1950) and Local Indicators of Spatial Associations (LISA) (Anselin, 1995) were applied to examine statistical significance of spatial patterns. Geographically weighted regression (GWR) (Fotheringham, Brunsdon, & Charlton, 2003) was lastly utilized as a local regression model to extend the results of the conventional OLS-based approach.

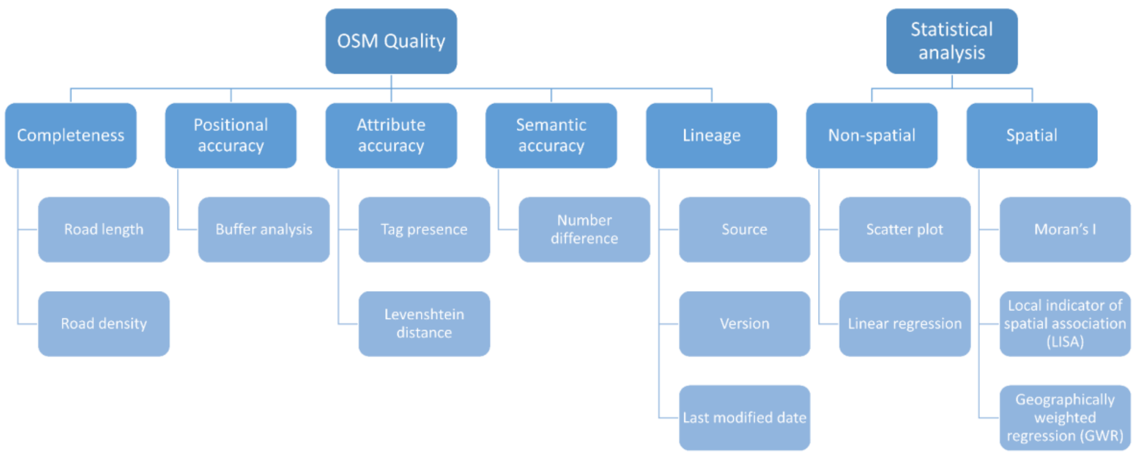

Figure 10. Methods of the national study

3.3 Results and discussion

3.3.1 Canadian OSM quality

3.3.1.1 Completeness

Figure 11 illustrates the total road length differences between the source and reference datasets. A positive number means DMTI has a longer road length, and a negative number represents OSM has better completeness. Results are aggregated based on DMTI's road classification (Table 9). Only motorways are included because the number of trails in OSM is much more than that in DMTI. This situation was also identified in the U.S. (Zielstra & Hochmair, 2012) and Germany (Neis et al., 2011). A significantly higher number of total road lengths in DMTI can be observed, which is consistent with previous findings in Germany (Neis et al., 2011; Zielstra & Zipf, 2010) and the U.S. (Zielstra et al., 2013). However, H. Zhang and Malczewski (2017) found that in London, Ontario, OSM had a longer total road length, which indicates the spatial heterogeneity of OSM quality in Canada. In the same study, the unclassified OSM roads were discovered to be mainly local roads through manual examination (H. Zhang & Malczewski, 2017), which may be the case nationally as well.

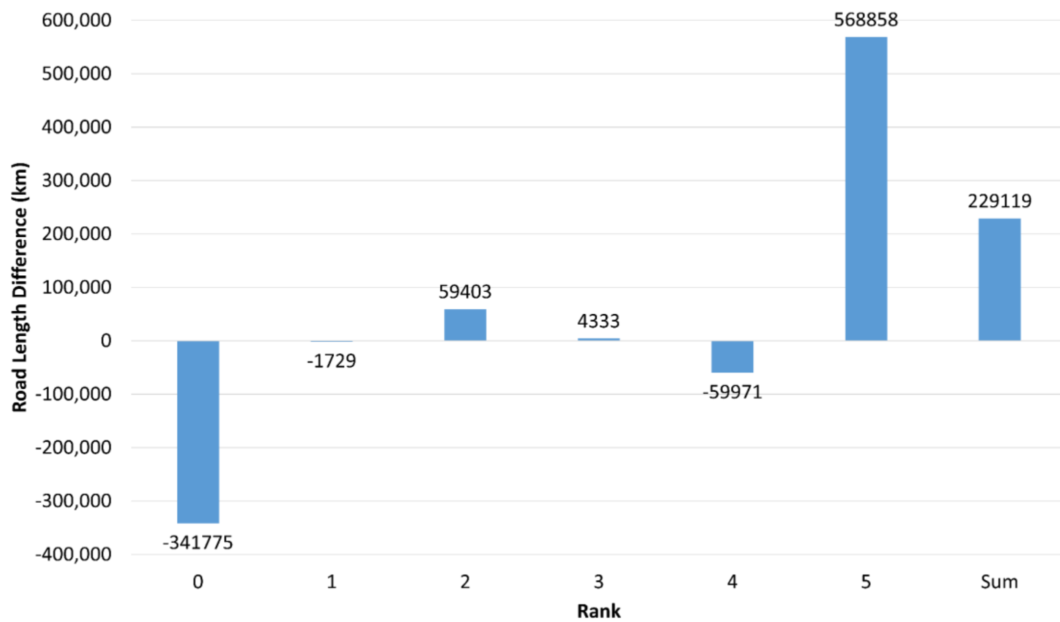

Figure 11. Classified national road length differences

Using a cell size of 250 m, Figure 12 shows the spatial distribution of the differences in road density. The top and bottom 0.5% of the data have been removed to reduce the effects of outliers. Here, green pixels represent a higher road density of DMTI; pink pixels represent a higher road density of OSM; and yellow pixels represent no difference. The maximum absolute value of green pixels (4.12) is significantly larger than that of pink pixels (0.52), indicating that the overall road density of DMTI is higher than that of OSM. In many cases, urban regions such as the Great Toronto Area (GTA), Ottawa and Quebec City have higher road densities in OSM, while remote regions such as the northern territories have higher road densities in DMTI. This pattern is similar to the OSM street networks of Germany in 2009, where completeness ranged from 97% in densely populated zones to 18% in uninhabited areas (Ludwig et al., 2011). Saskatchewan has an “anomalous” spatial pattern where OSM generally outperforms DMTI in road density. One potential explanation is the more up-to-date roads in Saskatchewan – in fact, 81% of streets in the province have been created between 2012 and 2013, whereas in Alberta, 85% of streets have been added to the database by 2009 (Gröchenig et al., 2014a).

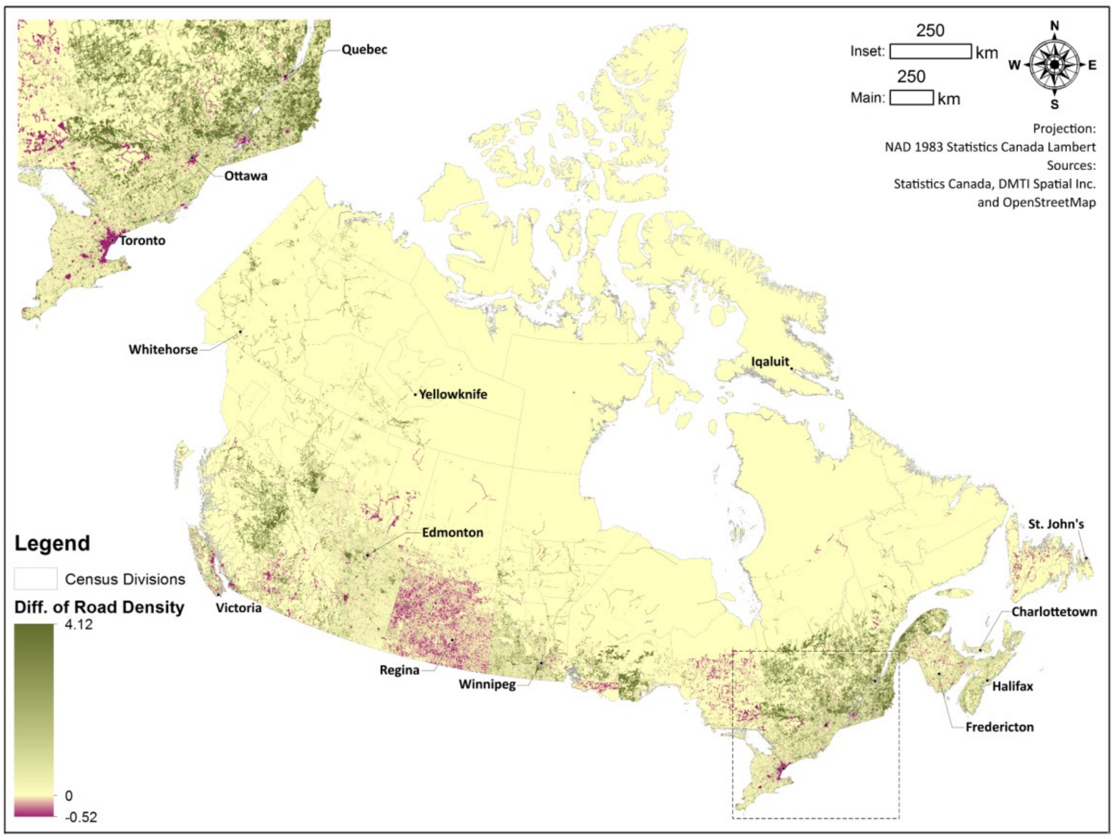

Figure 12. National differences of road density

3.3.1.2 Positional accuracy

Figure 13 shows the results of the buffer analysis. Approximately 60% of roads of DMTI have a 25-m or better positional accuracy, while the rest have a guarantee of 25 to 30-m accuracy. Overall, 91.5% of roads of OSM fall within the 30-m buffer, in which 77.5% are within 5 m, 8.3% between 5 and 10 m, and 5.7% between 10 and 30 m away from the reference dataset. Compared to Germany in 2009, the Canadian OSM streets have a 4.5% increase in positional accuracy within the 5-m buffer, but a 8.5% decrease in total – all German OSM streets were within the 30-m buffer of Navteq data (Ludwig et al., 2011). In terms of road classification, primary and secondary highways have relatively low positional accuracy, whereas local roads are the most accurate ones. This phenomenon can probably be explained by Linus' Law, which was found to generally apply to positional accuracy in London, England (Haklay et al., 2010).

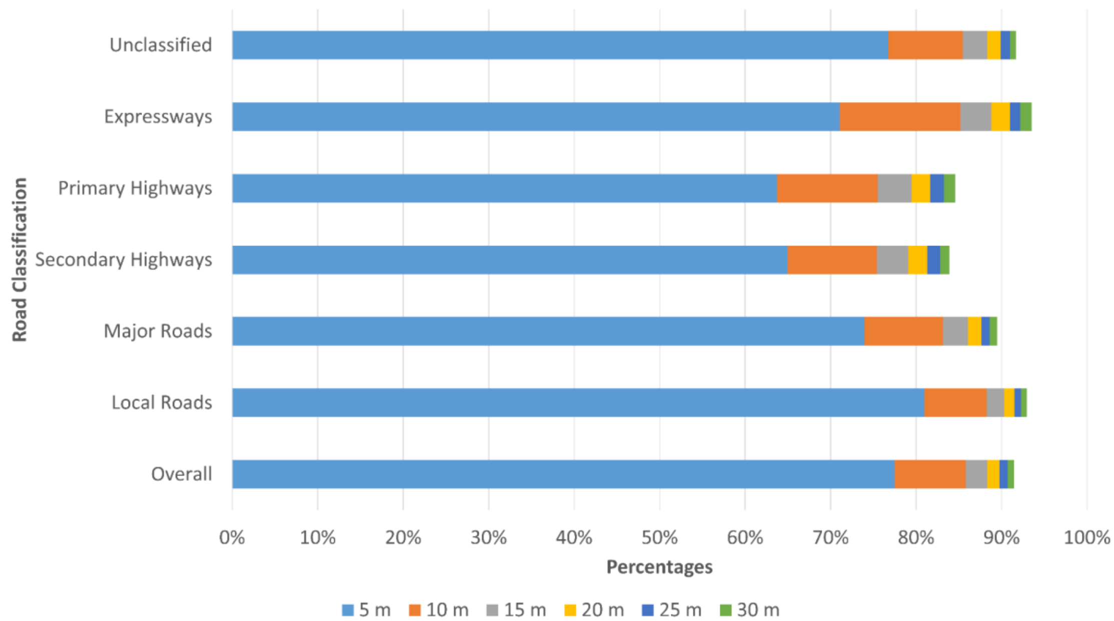

Figure 13. National results of the buffer analysis

3.3.1.3 Attribute accuracy

Figure 14 shows the tag presence rates of Canadian OSM street names, which have been divided into five components to match the attributes in DMTI. For the most part, French road names have prefix street types, and English road names have suffix street types. In comparison to London, Ontario (H. Zhang & Malczewski, 2017), the national tag presence rates dropped from mostly 90% and above to a minimum of 52%, which once again indicates the spatial heterogeneity of the Canadian OSM quality. Suffix directions have close tag presence rates both locally and nationally. This may suggest OSM contributors either do not know or do not care about most of the suffix directions of

Canadian streets. Core street names and suffix street types have the highest presence rates, which is understandable since a common street name consists of the two components. Like the results in Section 3.1.2 and the French study by Girres and Touya (2010), Linus' Law plays a role in attribute accuracy as well. Primary and secondary highways usually have lower tag presence rates, while major and local roads have higher percentages of presence, except for core street names which are potentially influenced by the data import from GeoBase. Neis, Zielstra, and Zipf (2011) discovered that unclassified roads had the highest ratio (61%) of missing names or route numbers in Germany in 2011, which is not the case in Canada. Overall, the tag presence rates of Canadian OSM street names are comparable with those in Germany (82.5% to 94.4%) in 2009 (Ludwig et al., 2011).

Figure 15 shows the Levenshtein distance of the Canadian OSM street names. Prefix and suffix directions, with a maximum text length of 1, have almost perfect spelling accuracy. The percentages of completely matched prefix and suffix street types and core street names are about 87%, 71% and 57% respectively. A Levenshtein distance from 1 to 3 usually represents a typo (Girres & Touya, 2010). Some extreme Levenshtein distance with a maximum value of 79 were identified in core street names; however, this component also has the largest maximum text length. The average Levenshtein distance of core street names is 3.09, which is higher than that of core street names (0.80) in London, Ontario (H. Zhang & Malczewski, 2017).

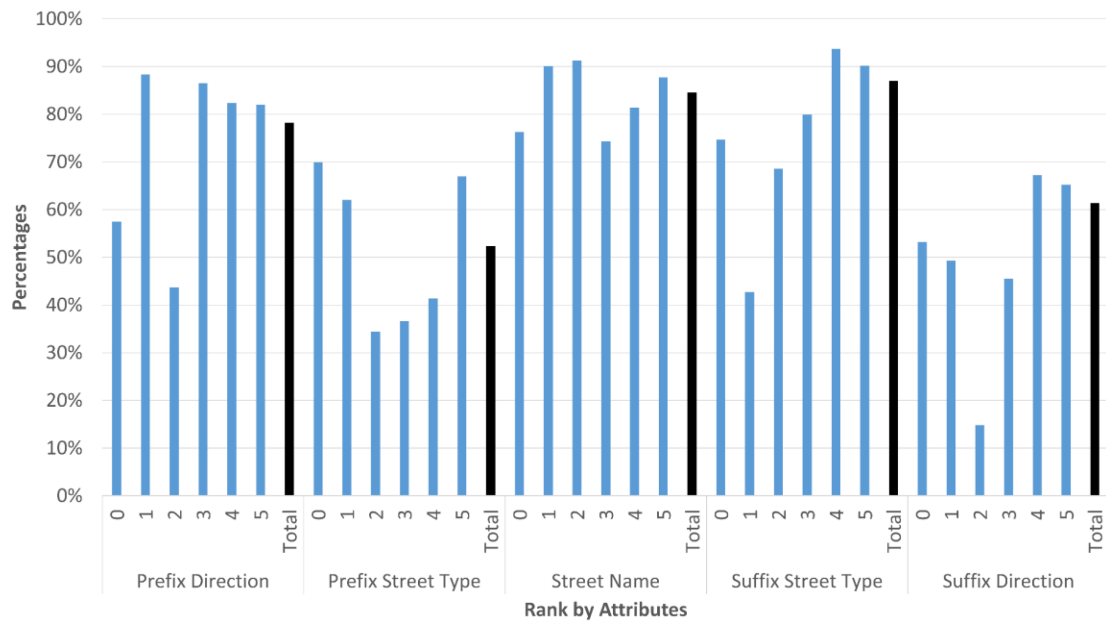

Figure 14. National tag presence rates of street names

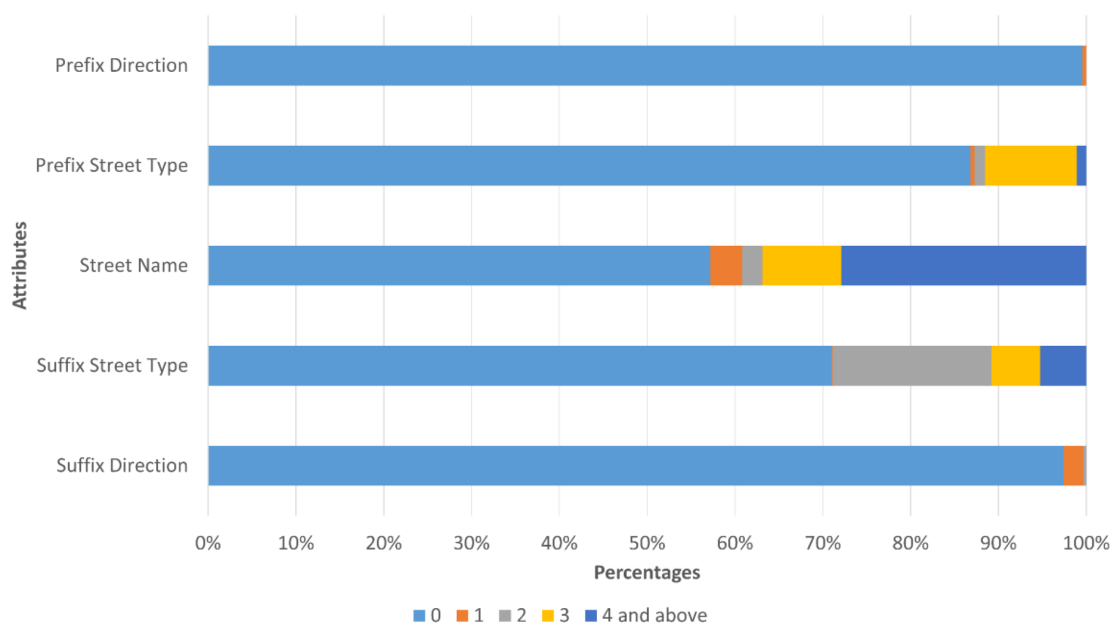

Figure 15. National levenshtein distances of street names

3.3.1.4 Semantic accuracy

Table 13 shows the absolute number differences of numeric attributes between OSM and DMTI street segments. A difference of 5 in rank is due to the unclassified roads in OSM;

other than this, the major difference is 1, which is understandable because of the incompatible classification schema (Girres & Touya, 2010) and classification ambiguity and conceptual plausibility (Ali et al., 2014). Another possibility behind the misclassification is the import from GeoBase, which was the case with the TIGER/Line import in the U.S. (Zielstra et al., 2013). The completeness of number of lanes in OSM is significantly higher than that in DMTI, which resulted in the low 40% matched rate. Because of the same reason, the semantic accuracy of presented number of lanes in OSM cannot be fully evaluated; the results only indicate that two is the most common number of lanes. In contrast, tunnel, bridge and oneway flags have nearly perfect accuracy. It is worth noting that the total number of positive flags (value equals to 1) in both datasets is very small, which leads to this high accuracy.

Table 13. Number differences in Canada

Differences	Percentages	Differences	Percentages
Rank		Tunnel	
0	59.1%	0	100.0%
1	12.3%	1	0.0%
2	1.5%	Bridge	
3	0.4%	0	99.2%
4	0.1%	1	0.8%
5	26.6%	-	-
Number of Lanes		Oneway	
0	39.5%	0	99.2%
1	3.0%	1	0.8%
2	56.9%	2	0.0%
3 to 9	0.7%	-	-

3.3.1.5 Lineage

Figure 16 presents the percentage differences of selected quality metrics between GeoBase-sourced road segments (approximately 77% of the total) and the entire OSM dataset, which shows the impacts of data import on attribute and semantic accuracy. Completeness and positional accuracy were not included because of their aggregated results. Most quality measures have slightly improved accuracy percentage-wise, which is probably due to the removal of outliers from vandalism. Four quality measures have decreased accuracy, and require further exploration for logical explanations.

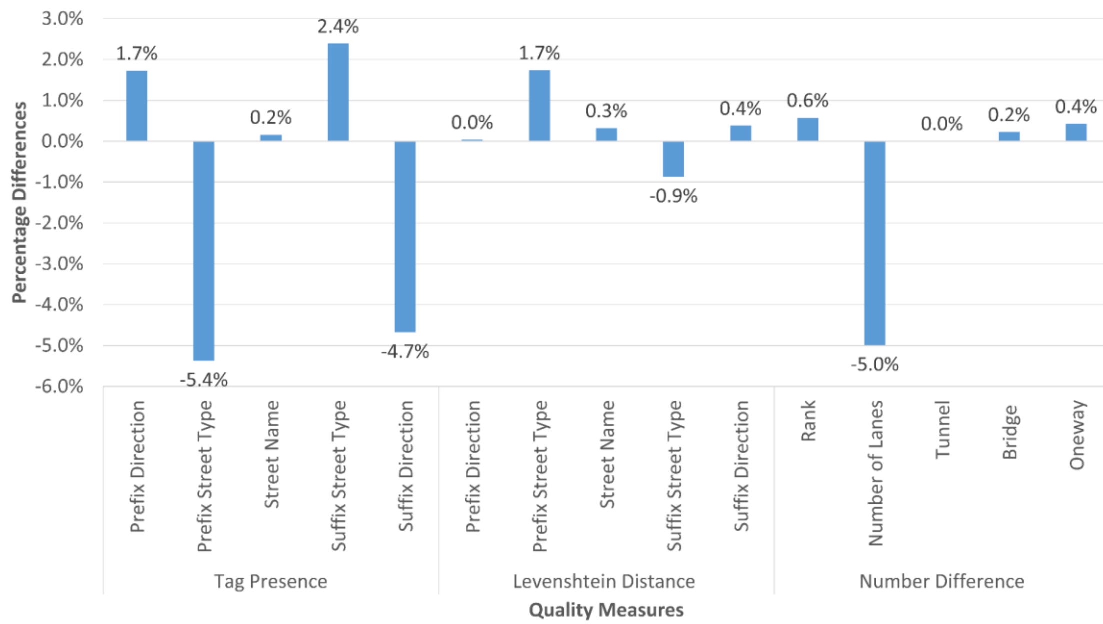

Figure 16. Percentage differences between GeoBase-sourced road segments and the entire dataset

3.3.2 Statistical analysis

3.3.2.1 Non-spatial analysis

After removing the outliers using box plots, scatter plots were created as the first step of the non-spatial analysis (see Figure 17). Results of quality measures and indicators were weighted by road length and aggregated at dissemination areas, which are the smallest standard geographic unit in Canada (Statistics Canada, 2015). In terms of the dependent variables, version represents the average number of times the road segments have been edited, and days represent the average number of days between the last edited date and Sep. 1, 2015. The explanatory variables include one result from each of the four quality measures: completeness, positional accuracy, attribute accuracy and semantic accuracy. The smaller the explanatory variables, the better the OSM quality. Thus, it is hypothesized that the OSM accuracy is negatively correlated with version and positively correlated with days. However, neither clear nor consistent relations were identified as most scatters are randomly distributed.

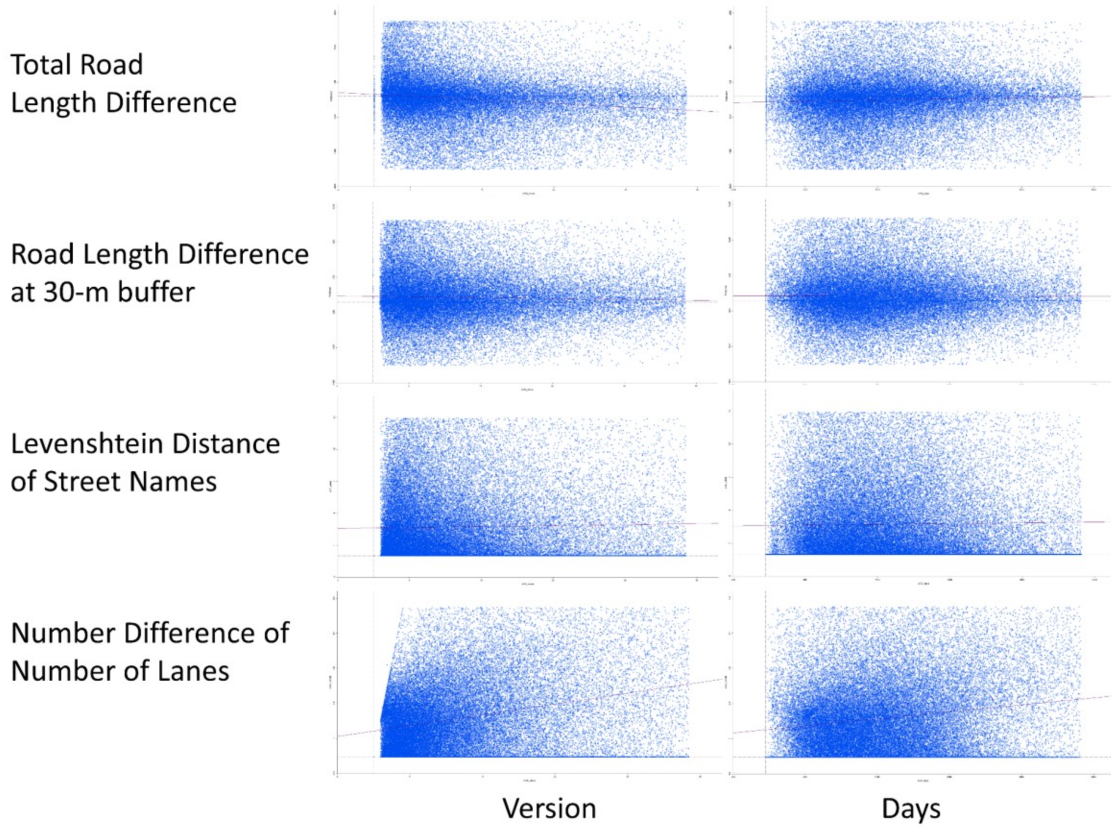

Figure 17. Scatter plot matrix

Multiple linear regression was applied to examine if two explanatory variables can explain the OSM extrinsic quality better than one. Table 14 shows the largest multiple R-squared value is 0.099, which means only approximately 10% of variability in semantic accuracy was explained by version and days. All but attribute accuracy have statistically significant p-values, but a very large number of observations with a p-value of 0.000 may not have any practical significance (M. Lin, Lucas Jr, & Shmueli, 2013). Therefore, multiple linear regression also has inconclusive results.

Table 14. Linear regression statistics

Quality Measures	**Completeness**	**Positional accuracy**	**Attribute accuracy**	**Semantic accuracy**
Sample Size	36707	39449	45611	47352
Multiple R-Squared	0.027	0.002	0.000	0.099
Prob (F-statistic)	0.000	0.000	0.344	0.000

3.3.2.2 Spatial analysis

Tables 15, 16 and 17 summarize the results of Moran's I, LISA and GWR respectively. Although all global spatial autocorrelation statistics are statistically significant, the R-squared values are extremely low, meaning that only a very small amount of extrinsic OSM quality (5.3% maximum) can be explained by the model. Like the multiple linear regression models, cautions are needed to interpret statistically significant p-values of large sample size. The Moran's I values indicate weak positive or negative spatial autocorrelation, which is inconsistent with the hypothesis in Section 3.3.2.1. LISA statistics are not representative as well – the majority of the tested dissemination areas have statistically insignificant results. No consistent regional patterns were identified. The same applies to GWR, where the majority of the local R-squared values are clustered below 0.5. High R-squared values were spotted in the models of attribute accuracy and semantic accuracy, but the results spatially contradict each other.

In summary, both analyses did not prove the assumption that there is a relationship between quality measures and indicators, and the spatial analysis did not identify any consistent local impacts on the global results. This finding differs from the work of Keßler, Theodore, and Groot (2013). However, Mullen et al. (2015) could not find statistically significant relationships between OSM quality and demographic variables as well, and one of their explanations is that contributions from remote mappers without local knowledge substantially increased the complexity of OSM quality. In the case of Canada, data import can potentially be a more essential factor since bots are able to create various types of systematic errors, which can be difficult when tracking and understanding from the perspective of human behaviors.

Table 15. Moran's I statistics

Indicators	**Version**				**Days**			
Measures	C	PA	AA	SA	C	PA	AA	SA
Sample Size	39298	42180	48073	49637	41507	44482	49934	51074
R-Squared	0.053	0.012	0.010	0.021	0.001	0.002	0.000	0.008
Moran's I	-0.129	-0.051	-0.052	0.113	0.014	-0.018	-0.010	0.070
Prob (b)	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000

Table 16. LISA statistics

Indicators	Version				Days			
Measures	C	PA	AA	SA	C	PA	AA	SA
Insignificant	81.5%	86.6%	64.9%	55.1%	81.0%	86.9%	64.3%	56.0%
High-High	1.8%	1.9%	3.5%	9.5%	4.3%	3.3%	5.7%	9.5%
Low-Low	4.3%	3.3%	13.5%	17.5%	5.8%	2.9%	12.4%	14.8%
Low-High	6.8%	5.5%	8.8%	9.4%	4.3%	3.9%	6.9%	9.0%
High-Low	5.6%	2.7%	9.3%	8.4%	4.6%	3.0%	10.7%	10.8%

Table 17. Local R-Squared statistics of GWR

Measures	C	PA	AA	SA
Minimum	0.000	0.000	0.000	0.000
Maximum	0.549	0.182	0.920	0.985
Mean	0.041	0.012	0.148	0.289
Standard Deviation	0.045	0.014	0.141	0.200

3.4 Summary and outlook

This study evaluated the extrinsic quality of the Canadian OSM street networks in terms of completeness, positional accuracy, attribute accuracy and semantic accuracy. The overall OSM quality in Canada is comparable with DMTI, although spatial heterogeneity is a common theme across all quality measures. Urban areas received more contributions than rural areas, and footways were favored over motorways by contributors in general. The extrinsic quality results were then analyzed with intrinsic quality indicators to explore the possibility of using trust as proxies for OSM quality assessment at a small scale, but failed to identify any statistically significant relationships between tested variables. As an exception, GeoBase-sourced road segments have lightly and commonly improved quality. For future work, other features, such as buildings and points of interest, can be evaluated. Measures such as temporal quality and logical consistency can be examined in addition. Lastly, non-linear models can be tested in non-spatial and spatial analyses.

While this study does not support users in determining the OSM quality in Canada using its editing history, the validity of intrinsic quality indicators should continue being explored. Results of this study also have some implications on OSM quality improvement in the future. For instance, do the activities of remote mappers decrease the overall quality of the project? Is local knowledge necessary to create accurate maps? How can the uniformity of OSM quality be increased? Are strict specifications better or worse for the project, and should contributors have their current degree of freedom? While data import boosts up the number of map features dramatically in a short period, does this action impair the motivations of OSM contributors and the sustainability of the project in the long term? These questions are worth discussing and can potentially contribute to quality improvements in VGI.

Chapter 4

4 Conclusions

4.1 Revisiting study objectives

There were four objectives of this research: (1) to examine the reliability of the Canadian OSM data in two different scales, (2) to compare the quality of the Canadian OSM road networks with the quality in other locations, (3) to validate new approaches of intrinsic quality evaluation in VGI, and (4) to establish implications of quality control for future VGI project development. The objectives were reflected in this thesis. Chapters 2 and 3 provided analyses on the quality of the Canadian OSM data in different scales, and the national and metropolitan results were compared in Chapter 3. Both Chapter 2 and 3 offered discussions of the differences and similarities between the OSM quality in Canada and other regions. Intrinsic quality indicators, such as provenance metadata, were examined with extrinsic quality measures in Chapter 3. The concluding chapter provided implications for VGI quality improvement.

4.2 Summary of findings

This thesis uses a municipal and a national study to examine the quality of OSM road networks. Generally, the OSM quality is closely ranked with DMTI road lines, and the reliability of OSM editing history as a source of data trust cannot be statistically verified. Comparing the two studies, the national OSM quality is not as good as that in London, Ontario, and spatial heterogeneity is commonly applicable in terms of analyzed quality measures. The main reason behind this conclusion is the participation inequality. Although densely populated areas sometimes have an equal or better quality than DMTI, remote areas can have much worse data quality than the reference dataset. Additionally, issues may be caused by data import and “armchair mapping”. Hence, it is very difficult to generalize the OSM quality, and a fitness-of-use quality assessment is essential if OSM is to be considered for application to a project with higher than usual demands for map accuracy.

4.3 Limitations

There are some limitations to this study. The main issue is that the assessment results may not be applicable in all cartographic product selection processes. In terms of map features, motorways were the focus of this study due to the lack of reference dataset for footways. Other features in the form of nodes (e.g., schools), ways (e.g., buildings) and relations (e.g., bus routes) were not evaluated as well. With regard to quality measures, some criteria, such as logical consistency and temporal quality, were not tested, and some criteria can be further assessed. For example, semantic accuracy is actually very complex because of the classification ambiguity and conceptual plausibility, so number difference is only a starting point. Individuals have various “senses of place” and may have quite different definitions of road classification or boundaries of urban centers. Regarding the methodology, the details of feature matching were not covered since the study implemented the black-box algorithms in ArcGIS. Matching errors were unavoidable because of the impossibility of manual matching accuracy validation at the national level. Other extrinsic methods in Tables 5, 6 and 7 can be tested and compared, and the reliability of intrinsic quality indicators can be further explored in non-linear models. The intrinsic indicators are especially important in places where a reference is unavailable, and even with an accessible reference, it is not 100% accurate (e.g., the 30-m positional accuracy in DMTI).

4.4 Contributions

This study is the first attempt to examine both extrinsic and intrinsic quality evaluation of OSM at the Canadian national level. Feasible methods are identified and implemented for future VGI quality assessment as well as geocomputation using big data. Results of this research can be compared with studies in previous years and/or various locations to understand the development of OSM quality over time and the heterogeneity across space. Contributors can learn from the Canadian example and improve OSM quality in the future. Governments, enterprises and other organizations can also use the presented results for decision-making in cartographic product selection. Broadly speaking, this thesis provides deeper insights into the accuracy and uncertainty of VGI and GIS.

4.5 Future research directions

Table 18 summarizes the ex ante and ex post approaches of VGI quality improvement (adapted from Bordogna et al., 2016). The ex ante strategies are designed before VGI contributions to reduce errors. For example, Kort is a gamified mobile web application for fixing erroneous OSM data. Players can collect points (also known as Koins) after completing tasks such as finding a speed limit of a road segment and filling in the missing names of points of interest (OpenStreetMap, 2017c). Huang, Kanhere, & Hu (2010) proposed a reputation system for trustworthiness evaluation of VGI. Using the RFSN framework (Ganeriwal, Balzano, & Srivastava, 2008), a watchdog module was first created to detect outliers. Node ratings generated from the watchdog module were then imported into a reputation module to calculate node quality in a time series. In Wikimapia, third party validation has already been implemented, where users can vote for other users as positive feedback for their contributions to the project (Flanagin & Metzger, 2008). Vandecasteele & Devillers (2015) designed a recommender system for OSM with two major functions. Similar tags are suggested for contributors based on existing tags, and a notification is sent to map editors if the similarity between existing tags is too low. To solve data import issues, Zielstra et al. (2013) recommended vector map tracing instead of bot mapping. However, contributors may lose interest because the excitement of content creation is taken away in this case. For future research, systems in the examples should be enhanced, and new tools should be developed to prevent errors before volunteered information contribution. Fitness-of-use specifications are especially important as the demands of map accuracy vary greatly from one project to another.

Table 18. Strategies of VGI quality improvement

Ex ante strategies	• Training; checklists; gamification (Neis & Zielstra, 2014) • External knowledge • Automatic error checking • Usage of sensors • Volunteer reputation and motivation (Flanagin & Metzger, 2008; Huang, Kanhere, & Hu, 2010) • Explicit specifications featuring fitness-of-use (Devillers & Jeansoulin, 2006; Girres & Touya, 2010; Senaratne et al., 2016) • Third party validation (Bishr & Kuhn, 2007; Fogg & Tseng, 1999; Spielman, 2014) • Recommender system (Kalantari, Rajabifard, Olfat, & Williamson, 2014; Vandecasteele & Devillers, 2015) • Vector map tracing (Zielstra et al., 2013) • Collaboration events (e.g., mapping parties)
Ex post strategies	• Ranking volunteers' contributions • Data mining (Basiri et al., 2016; Coleman, 2010; Neis, Goetz, & Zipf, 2012) • Fusion of redundant information • Enrichment (geocontext; trusted sources) • External knowledge • Linked data infrastructure (Idris, Jackson, & Ishak, 2014) • Provenance visualization (Flanagin & Metzger, 2008)

The ex post strategies are methods of error reduction after the collection of VGI. For instance, Neis, Goetz, & Zipf (2012) developed a vandalism detection system for OSM and found that at least one (intentional or unintentional) vandalism activity was identified each day within a 7-day period. Idris, Jackson, & Ishak (2014) suggested allowing users to make their own decisions on the correctness of VGI based on linked data and information on the World Wide Web. Flanagin & Metzger (2008) mentioned the Wiki Dashboard for Wikipedia, and a similar tool can be developed to reveal historical editing patterns implicating VGI credibility. For future research, data mining and machine learning are the forefront techniques that should be applied to error reduction in VGI.

The pressing concerns about OSM are retaining long-term contributors, cultivating more serious mappers, and determining the necessity of local knowledge in volunteered mapping. It is easy to start a project, but it is hard to maintain it. Although the number of registered users on OSM continues to grow linearly, many contributors abandon the project within a short period of time, and the number of serious mappers remains low (Neis & Zipf, 2012). For future research, both qualitative and quantitative approaches should be implemented in the demographic analysis of serious OSM mappers. Motivations of long-term and active contributors need to be determined, so OSM can be better designed to attract new members and retain existing users.

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Appendices

Appendix A: Summary of recent literatures on quality analysis of OSM

Studies	Time	Study Areas	Reference Data Sources	Data Types			Quality Criteria or Methodology						
				POI	Line	Poly	C	PA	AA	LC	SA	TQ	L
Amelunxen (2010)	N/A	North Rhine-Westfalia, Germany	Geocoding service by Google	x				x					
Cipełuch, Jacob, Mooney, & Winstanley (2010)	2010	Ireland	Google Maps and Bing Maps		x		x		x	x			
Girres & Touya (2010)	2009	France	BD TOPO	x	x	x	x	x	x	x	x	x	x
Haklay (2010)	2007	England, UK	OS Meridian 2		x		x	x					
Haklay, Basiouka, Antoniou, & Ather (2010)	2007	London and England, UK	OS Meridian 2		x		Relationship between average positional error and number of contributors						
Mooney, Corcoran, & Winstanley (2010)	2010	European regions	N/A		x	x			x	x			
Zielstra & Zipf (2010)	2009	Germany^	Tele Atlas		x		x					x	
Antoniou (2011)	2009	England, UK	OS Meridian 2		x			x		x			
Ludwig, Voss, & Krause-traudes (2011)	2009	Germany^	Navteq		x		x	x	x				
Mondzech & Sester (2011)	N/A	Germany	ATKIS		x		Accessibility and length of simulated routes						
Neis, Zielstra, & Zipf (2011)	2007 to 2011	Germany^	TomTom		x		x			x		x	
Hayakawa, Imi, & Ito (2012)	2012	Japan and other regions	N/A	x	x	x	x						
Helbich, Amelunxen, & Neis (2012)	N/A	Germany	Tele Atlas		x			x					

Studies	Time	Study Areas	Reference Data Sources	Data Types			Quality Criteria or Methodology						
				POI	Line	Poly	C	PA	AA	LC	SA	TQ	L
Koukoletsos, Haklay, & Ellul (2012)	N/A	London and Newcastle, UK	OS ITN layer of MasterMap		x		x						
Mooney & Corcoran (2012a)	2011	UK and Ireland	N/A (User behavior)		x		Correlation between numbers of contributors and numbers of tags						
Mooney & Corcoran (2012b)	2011	UK, Ireland, Germany and Austria	N/A		x	x			x				
Siebritz et al. (2012)	2006 to 2011	South Africa	NMA	x	x							x	
Canavosio-Zuzelski, Agouris, & Doucette (2013)	2011	Purdue University, US	USGS National Map and TIGER/Line		x			x					
Corcoran, Mooney, & Bertolotto (2013)	2007 to 2011	Ireland	N/A		x							x	
Estima & Painho (2013, 2015)	2013	Portugal^	CLC	x					x				
Hecht, Kunze, & Hahmann (2013)	2011, 2012	Germany	Official building polygon dataset and ATKIS			x	x					x	
Hochmair & Zielstra (2013)	2012	Florida, US	TomTom, NAVTEQ, ESRI and TIGER/Line	x			x					x	
Jackson et al. (2013)	2011	Denver, US	ORNL	x			x	x					
Jokar Arsanjani, Barron, Bakillah, & Helbich (2013)	2012	Heidelberg, Germany	BKG		x		x	x			x		
Jokar Arsanjani, Helbich, Bakillah, Hagenauer, & Zipf (2013)	2012	Vienna, Austria	GMESUA			x			x				

Studies	Time	Study Areas	Reference Data Sources	Data Types			Quality Criteria or Methodology						
				POI	Line	Poly	C	PA	AA	LC	SA	TQ	L
Keßler, Theodore, & Groot (2013)	2011	Münster, Germany	N/A (Data trust and vandalism)	x	x	x	Trustworthiness (e.g., versions, users, confirmations and tag corrections)						
Pourabdollah, Morley, Feldman, & Jackson (2013)	N/A	UK^	OS VMD		x				x				
Touya & Brando-Escobar (2013)	N/A	France	N/A	x	x	x	Level of Details						
Wang, Li, Hu, & Zhou (2013)	N/A	Wuhan, China	NavInfo		x		x	x	x				
Zielstra, Hochmair, & Neis (2013)	2006 to 2012	US^	TIGER/Line		x		x						
Barron, Neis, & Zipf (2014)	2007 to 2013	US, Spain, Cameroon	N/A (Framework)	x	x	x	x	x	x	x		x	
Fan, Zipf, Fu, & Neis (2014)	2013	Munich, Germany	ATKIS			x	x	x		x	x		
Forghani & Delavar (2014)	N/A	Tehran, Iran	Municipality of Tehran		x		x	x		x			
Jilani et al. (2014)	N/A	London and East Essex, UK	N/A		x				x		x		
Jokar Arsanjani & Bakillah (2014)	2013	Baden-Württemberg, Germany	N/A (User behavior)	x	x	x	Logistic regression relationship between highly contributed areas and socio-economic variables						
Quattrone, Mashhadi, Quercia, Smith-Clarke, & Capra (2014)	2007 to 2012	London, UK	N/A	x								x	
Tenney (2014)	N/A	Canada^	NRN (2011)		x		x	x	x				
Zhou, Huang, & Jang (2014)	N/A	China	National basic data		x		x	x	x	x			

Studies	Time	Study Areas	Reference Data Sources	Data Types			Quality Criteria or Methodology						
				POI	Line	Poly	C	PA	AA	LC	SA	TQ	L
Ballatore et al. (2015)	2015	Germany and UK	N/A (Framework)		x		Conceptual quality: accuracy, granularity, completeness, consistency, compliance and richness						
Camboim, Meza Bravo, & Sluter (2015)	2015	Brazil	IBGE		x	x	x		x			x	
Dorn, Törnros, & Zipf (2015)	2014	Rhine-Neckar, Germany	ATKIS			x	x		x				
Eckle & De Albuquerque (2015)	N/A	Germany	Map from expert mapper			x	x	x					
Hashemi & Ali Abbaspour (2015)	2014	Wörrstadt, Germany	N/A (Framework)	x	x	x				x			
Hochmair, Zielstra, & Neis (2015)	2013	Portland and Miami, US	Buehler & Pucher (2012)		x		x						
Jokar Arsanjani, Helbich, Bakillah, & Loos (2015)	2007 to 2012	Heidelberg, Germany	N/A	x	x	x						x	
Jokar Arsanjani, Mooney, Zipf, & Schauss (2015)	2013	Germany	GMESUA			x	x		x				
Jokar Arsanjani & Vaz (2015)	2013	European cities	GMESUA			x	x		x				
Kalantari & La (2015)	2013	Victoria, Australia	Victorian governmental data			x	x	x	x	x			
Mashhadi, Quattrone, & Capra (2015)	2007 to 2012	London, UK	Navteq and Yelp	x			x					x	
Meier (2015)	N/A	Waterloo, Canada	NRN		x		x	x					
Mohammadi & Malek (2015)	2012	Tehran, Iran	N/A	x	x	x		x					

Studies	Time	Study Areas	Reference Data Sources	Data Types			Quality Criteria or Methodology						
				POI	Line	Poly	C	PA	AA	LC	SA	TQ	L
Mullen et al. (2015)	2011	Denver, US	ORNL	x			Non-spatial and spatial regression relationships between demographic characteristics and C and PA of OSM						
Parr (2015)	2006 to 2013	US^	US census and governmental data	x	x	x	The Activity-Context-Geography Model						
Sehra, Singh, & Rai (2015)	N/A	India	Ground data by smartphone		x		x	x	x				
Vaz & Jokar Arsanjani (2015)	2013	Toronto, Canada	DMTI Spatial Inc.			x			x				
El-Ashmawy (2016)	N/A	Saudi Arabia	Self-collected surveying data	x	x	x		x					
Yang, Fan, & Jing (2016)	2010 to 2014	Germany, France and UK	N/A (User behavior)	x	x	x	Use practice, skill and motivation as themes to identify the contributors' level of expertise						
Zhao, Zhou, Li, & Xing (2016)	2006 to 2014	Berlin, Germany and Pakistan	N/A (Data trust and vandalism)	x	x	x	Trustworthiness (e.g., contributor reputations)						

Note. ^: a national study

Appendix References

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